MEGA-BENCH: SCALING MULTIMODAL EVALUATION TO OVER 500 REAL-WORLD TASKS

Anonymous authors
Paper under double-blind review

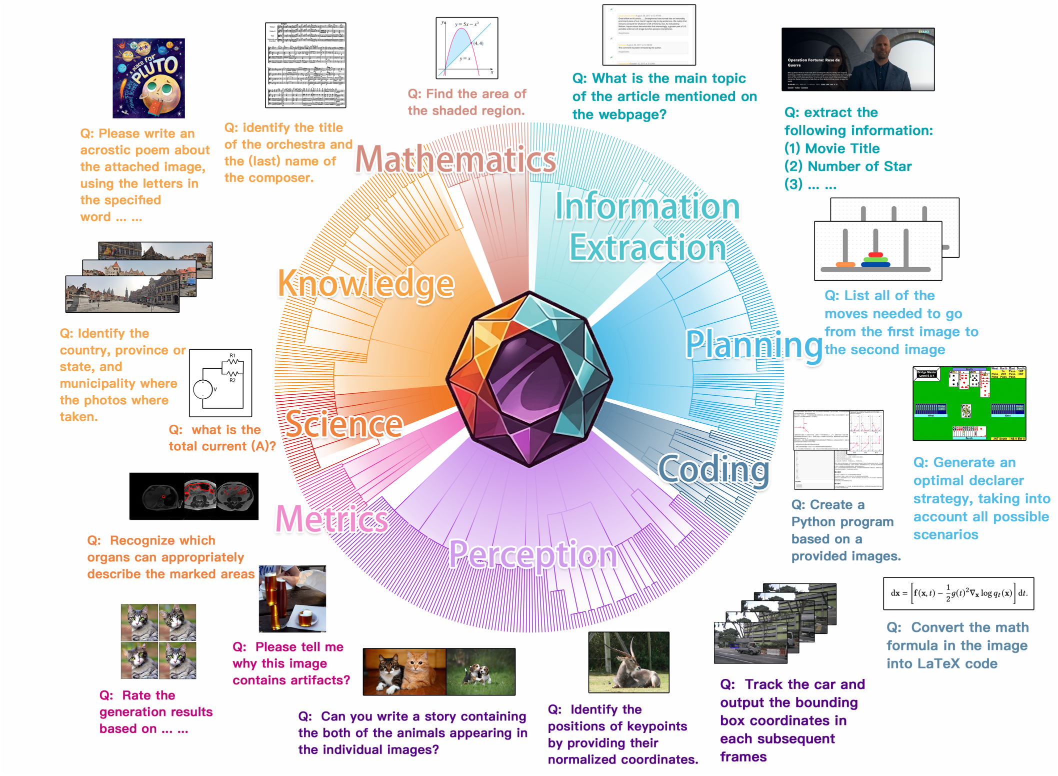

Q: Please write an acrostic poem about the attached image, using the letters in the specified word … …
Q: identify the title of the orchestra and the (last) name of the composer.
Q: Find the area of the shaded region.
Q: What is the main topic of the article mentioned on the webpage?
Q: extract the following information: (1) Movie Title (2) Number of Star (3) … …
Mathematics
Information Extraction
Knowledge
Planning
Q: List all of the moves needed to go from the first image to the second image
Q: Identify the country, province or state, and municipality where the photos where taken.
Q: what is the total current (A)?
Science
Coding
Q: Generate an optimal declarer strategy, taking into account all possible scenarios
Q: Create a Python program based on a provided images.
Metrics
Q: Recognize which organs can appropriately describe the marked areas
Perception
Q: Please tell me why this image contains artifacts?
Q: Rate the generation results based on … …
Q: Can you write a story containing the both of the animals appearing in the individual images?
Q: Identify the positions of keypoints by providing their normalized coordinates.
Q: Track the car and output the bounding box coordinates in each subsequent frames
Q: Convert the math formula in the image into LaTeX code

Figure 1: MEGA-Bench contains 505 multimodal tasks with diverse data sources, input/output formats, and skill requirements. The taxonomy tree guides and calibrates the annotation process.

ABSTRACT

We present MEGA-Bench, an evaluation suite that scales multimodal evaluation to over 500 real-world tasks, to address the highly heterogeneous daily use cases of end users. Our objective is to optimize for a set of high-quality data samples that cover a highly diverse and rich set of multimodal tasks, while enabling cost-effective and accurate model evaluation. In particular, we collected 505 realistic tasks encompassing over 8,000 samples from 16 expert annotators to extensively cover the multimodal task space. Instead of unifying these problems into standard multi-choice questions (like MMMU, MMBench, and MMT-Bench), we embrace a wide range of output formats like numbers, phrases, code, LaTeX, coordinates, JSON, free-form, etc. To accommodate these formats, we developed over 40 metrics to evaluate these tasks. Unlike existing benchmarks, MEGA-Bench offers a fine-grained capability report across multiple dimensions (e.g., application, input type, output format, skill), allowing users to interact with and visualize model capabilities in depth. We evaluate a wide variety of frontier vision-language models on MEGA-Bench to understand their capabilities across these dimensions.

1 INTRODUCTION

Large foundation models (OpenAI, 2023; 2024a; Anthropic, 2024a; Google, 2023; Meta, 2024; Alibaba, 2024) have dramatically transformed the landscape of artificial intelligence by showcasing exceptional capabilities across various tasks and domains. Originating in the realm of natural language processing, these models have progressively expanded to perceive and interpret multimodal information, including single images, multiple images, and videos. Previously, multimodal models were mainly used for standardized tasks like image captioning (Lin et al., 2014), video captioning (Wang et al., 2019), and visual question answering (Antol et al., 2015; Goyal et al., 2017; Xiao et al., 2021). With the recent progress on multimodal alignment, these models have shown great potential to solve many diverse and complex tasks with well-designed prompts. As a result, people have applied them to assist with many realistic tasks like “web navigation” (Koh et al., 2024), “game playing” (Valevski et al., 2024), “travel planning” (Xie et al., 2024), “visual navigation” (Wang et al., 2023a), “sports analysis” (Xia et al., 2024), “visual entity recognition” (Hu et al., 2023), “visual quality assessment” (Ku et al., 2024), and more. These efforts have significantly increased the utility of multimodal models.

An important challenge is identifying how to accurately gauge the abilities of these vision-language models (VLMs) across a wide range of tasks. Most existing benchmarks are designed to cover only one or a few similar tasks, making them inadequate for evaluating the models’ overall capabilities. The status quo is to evaluate the model on many existing benchmarks to showcase their all-round abilities. For example, Qwen2-VL[1] was evaluated on 27 image and video benchmarks in total. Although this massive evaluation effort provides valuable insights into how well these models handle specialized tasks, it also introduces a significant overhead and several challenges:

- **Limited Output Diversity**: The existing multi-task benchmarks like MMMU (Yue et al., 2024a), MMT-Bench (Ying et al., 2024) rely heavily on multiple-choice questions to lower the burden of evaluation. This fails to evaluate the generative abilities of these multimodal models.

- **Lack of Task Coverage**: The existing benchmarks are often sporadic and lack a systematic design to cover the multimodal task space. Certain abilities are not well covered in the current ecosystem. Consequently, even exhaustively testing all the available benchmarks would not be sufficient.

- **Expensive Inference Cost**: The full evaluation process is expensive regarding computation cost/-time or API expense. Since many examples or tasks are similar in the capabilities they assess (e.g., DocVQA Mathew et al. (2021) alone has thousands of examples for examining doc understanding and OCR-related abilities), overly repetitive evaluation at a large scale leads to resource waste.

- **Unmanageable Setups**: Each benchmark has complexities when setting up the evaluation. For example, VQA (Goyal et al., 2017) alone has four splits (val, dev-test, std-test, and test). It is hard to track the exact setup of different baseline models to ensure a fair comparison.

To address these challenges, we advocate for a unified protocol that scales up multi-modal evaluation to *maximize the task coverage and the diversity in model outputs while optimizing the inference cost*. As an initial attempt, we propose MEGA-BENCH, which is designed to provide a comprehensive and systematic assessment of multimodal foundation models.

To build MEGA-BENCH, we first construct a *task taxonomy tree* that organizes different multimodal tasks based on the application type (Figure 1), with significant effort spent adjusting and refining the taxonomy tree to ensure sufficient coverage and diversity. The task taxonomy tree then serves as the guiding principle to ensure all relevant tasks and skills are covered and appropriately balanced. To help the annotators create their tasks, we build an annotation GUI to simplify the process of creating the task JSON files and a web tool to visualize the results of the VLM’s responses alongside the ground truth. We also review each task contribution when it is first submitted, after evaluating the models on the new tasks, and periodically throughout the annotation process to ensure that all of the tasks are novel and high-quality. This collaborative effort resulted in the compilation of 505 realistic tasks, effectively covering (almost) the entire multimodal capability space at a manageable inference cost. To facilitate nuanced and precise evaluation, we also developed 45 *highly-customized metrics* tailored to these tasks during the annotation process.

Unlike existing benchmarks that often provide a single score, MEGA-BENCH offers a fine-grained capability report based on multiple dimensions such as the input type, input format, output format, and required skills. This interactive and visualizable report enables users to identify the models’

---

[1] https://github.com/QwenLM/Qwen2-VL

performance across several orthogonal dimensions, uncovering strengths and weaknesses that might be obscured in aggregate scores. Such detailed analysis is invaluable for researchers and developers aiming to enhance foundation models and optimize them for specific downstream applications.

Using MEGA-BENCH, we conducted comprehensive studies of popular flagship and efficiency models (with both open-source software and proprietary APIs) and identified some findings below:

1. Among flagship models, Claude 3.5 Sonnet (1022) and GPT-4o (0513) currently lead in performance across a wide range of multimodal tasks, with less than a 0.1% difference in their overall scores. Our detailed breakdown shows that Claude 3.5 Sonnet excels in planning and math with its latest upgrade bringing clear boosts in processing UI/Infographics inputs, while GPT-4o leads in information extraction and knowledge-intensive tasks.

2. Among open-sourced models, Qwen2-VL performs the best, with its performance near the top close-sourced flagship models, and outperforms the second best open-source model by $\approx$10%.

3. Among efficiency models, Gemini 1.5 Flash is the strongest model overall, except for the tasks related to handling User Interfaces and Documents.

4. Proprietary models can effectively leverage Chain-of-Thought (CoT) prompting to improve their performance, while open-source models hardly produce helpful reasoning processes. In our evaluation results, 10 of 13 open-source models get worse results with CoT prompting.

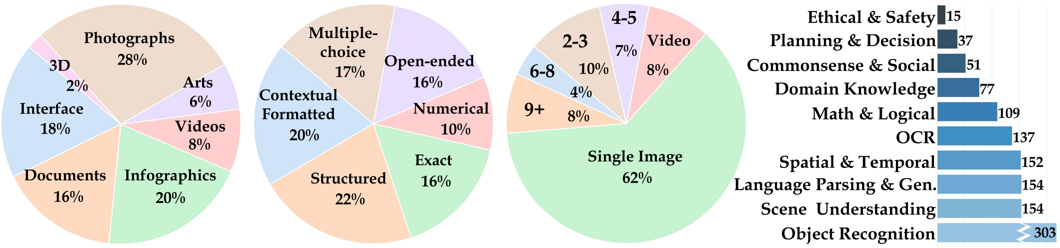
2 RELATED WORK

Multimodal benchmarks. Benchmarking in vision-language models has been a long-standing research problem. Before the era of large multimodal models, most benchmarks were designed for specific tasks or skills. Some benchmarks like VQA (Antol et al., 2015), GQA (Hudson & Manning, 2019), and ViswizVQA (Gurari et al., 2018) focus on photograph or natural images. ChartQA (Masry et al., 2022), InfoVQA (Mathew et al., 2022), DocVQA (Mathew et al., 2021), and OCR-VQA (Mishra et al., 2019) focus more on documents, infographics, and other similar media. Later on, there was a trend to build more well-rounded benchmarks to cover a wider range of skills or topics, such as ScienceQA (Lu et al., 2022), MMBench (Liu et al., 2023b), MMMU (Yue et al., 2024a;b), MMT-Bench (Ying et al., 2024), and more. However, due to the diversity of these different tasks, most benchmarks use multiple-choice questions for all problems. Therefore, these benchmarks cannot fully reflect the generational abilities of multimodal models. Complementary to this, LMsys arena (Chiang et al., 2024) and WildVision arena (Lu et al., 2024) have proposed to use user voting and Elo-ranking to benchmark multimodal models. Our benchmark is the first to scale up the tasks by a significant magnitude. Furthermore, our benchmark provides a breakdown report to analyze multimodal models across multiple dimensions.

Sensitivity of large model leaderboards to input format. Creating reliable leaderboards poses a substantial challenge for evaluating large models. Previous studies have noted that LLMs exhibit sensitivity to minor input modifications, including prompts and in-context examples in few-shot settings (Sclar et al., 2024; Chang & Jia, 2023). To mitigate input sensitivities, researchers have developed specialized prompt design and prompting-based training approaches (Liu et al., 2023a; Jain et al., 2024b). Nonetheless, for benchmarks that only allow a multiple-choice format (Wang et al., 2024d), studies by Zheng et al. (2024) and Robinson et al. (2023) find the option sequencing can significantly alter model rankings on the leaderboard. Recently, Alzahrani et al. (2024) explores the advantage of a hybrid scoring method to stabilize models' leaderboard rankings over input format. Though MEGA-BENCH does not include hybrid scoring for each individual task, the overall use of diverse and hybrid scoring methods and output formats across more than 500 tasks demonstrates *the robustness of the benchmark*.

3 MEGA-BENCH

MEGA-BENCH is a comprehensive multimodal benchmark that spans 7 input formats, 6 output formats, 10 different types of skills, and a varying number of visual inputs, whether single-image, multi-image or from video, as shown in Figure 2. Our benchmark covers 8 distinct subject areas in a hierarchical taxonomy to evaluate VLMs' ability to tackle various tasks.



(1) Input Format (2) Output Format (3) Visual Input Number (4) Skills

Figure 2: MEGA-BENCH's four keyword dimensions and the task-level statistics. The diversity along various dimensions enables fine-grained capability analysis.

3.1 BENCHMARK CONSTRUCTION PROCESS

Preparation. Figure 3 illustrates our annotation process. In the conceptualization stage, we propose a "draft" task taxonomy tree with the top two levels of Figure 1 by getting inspirations from existing multi-task or multi-discipline LLM/VLM benchmarks (Srivastava et al., 2022; Liu et al., 2023b; Yue et al., 2024a). The first level consists of general applications like "perception", "planning", "reasoning", etc., while the second level has more concrete meta-tasks like "document understanding", "app function understanding", "logic reasoning", etc. We host a brainstorming session to add exemplars under each second-level node and write descriptions about the number and quality of the tasks we expect. Based on our empirical observations of how general users use VLMs in real-world scenarios, we assign more task budgets to perception, knowledge, and information extraction than other first-level nodes while strictly monitoring the application-level distribution balance in the annotation process. We then distribute the second-level nodes in the "draft" tree to the annotators. This top-down framework minimizes overlaps between annotators and facilitates overall organization.

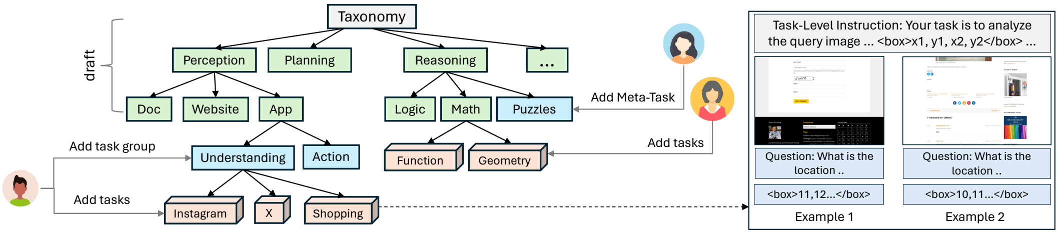


Figure 3: The annotation process of MEGA-BENCH. We propose a "draft" taxonomy tree and then distribute the second-level nodes to annotators. We allow the annotators to gradually refine the tree structure as they add new tasks. Each task has many examples and a shared task-level instruction. Each example has a question and a ground truth answer.

To ensure reliable commitment and annotation quality, we call up 16 designated expert annotators with rich LLM experience and computer science backgrounds. All annotators are graduate students or above with majors in computer science, electronics/communications engineering, bio-statistics, or finance, and 12 of them served as annotators or authors of LLM/VLM benchmarks published at top conferences. The annotators can 1) refine the "draft" taxonomy by adding/deleting nodes, 2) add "task group" nodes and then add a series of tasks under that, and 3) directly add tasks under an existing high-level node. We develop tools to facilitate the annotation process, including 1) an interactive annotation tool that defines the annotation format and automatically unifies all annotations into JSON files, 2) a GitHub repository to coordinate the task submission, reviewing, and discussion process, which was inspired by BIG-bench (Srivastava et al., 2022), and 3) a visualization tool that allows annotators to browse the existing tasks and the evaluation results of representative vision language models (VLMs). We coordinate all the annotators to ensure they understand our expectations and continuously improve our tools. Please see §B for complete details of annotation protocols.

Task annotation. The annotation process contains two rounds. The annotators submit tasks to the benchmark by creating pull requests (PR) to the main branch of our GitHub repository. In the first round of the annotation process, we ask the annotators to contribute 20 tasks following the principles below to ensure the quality of the task:

- *Data source and output format:* Creative tasks with diverse data sources and output formats are encouraged. If the data was collected from existing datasets, we ask annotators to adapt the original annotation into more specific questions and design more diverse answer formats.
- *Number of examples:* Each task should have at least 15 examples. Exceptions are allowed for some complicated tasks where the data are scarce.
- *Documentation:* Each task should be accompanied by documentation that indicates the source of the data, the capabilities the task tries to evaluate, and the evaluation metric to be used.

Our core contributors review each PRs carefully to provide feedback, and the accepted PRs are merged into the main branch. We periodically run the evaluation with commercial VLMs (e.g., GPT-4o) and update the results of existing tasks on our visualization page, which allows the annotators to better understand the difficulty of their tasks and catch potential glitches in the annotation. We found that this helps significantly improve the annotation quality.

Before the second round of annotations, the core contributors review all tasks in the taxonomy tree and investigate the biases in the task distribution. We then host another annotator session to propose new meta-tasks to balance the distribution and maximize the coverage. We then distribute the updated tree nodes to annotators and employ the same guidelines to finish the second-round annotations. After this round, each annotator contributes at least another 30 tasks.

Quality control and refinement. We leverage commercial VLMs to examine the task quality. Concretely, we gather the results of GPT-4o, Claude 3.5 Sonnet, and Gemini 1.5 Pro and compute an average score on each task. Tasks with almost 1.0 scores often have trivial questions (based on manual inspection) and can hardly distinguish the ability of different models. We ask the corresponding annotators to investigate and augment those tasks. For tasks with almost zero scores, the task reviewers audit them carefully and remove them if the zero score comes from incorrect annotations or insufficient instruction contexts. Finally, the benchmark contains a total of 505 tasks with roughly 8,200 examples, which is large enough to minimize the sample variance within each high-level taxonomy node. Please refer to §4.3 for an analysis of the number of examples per task.

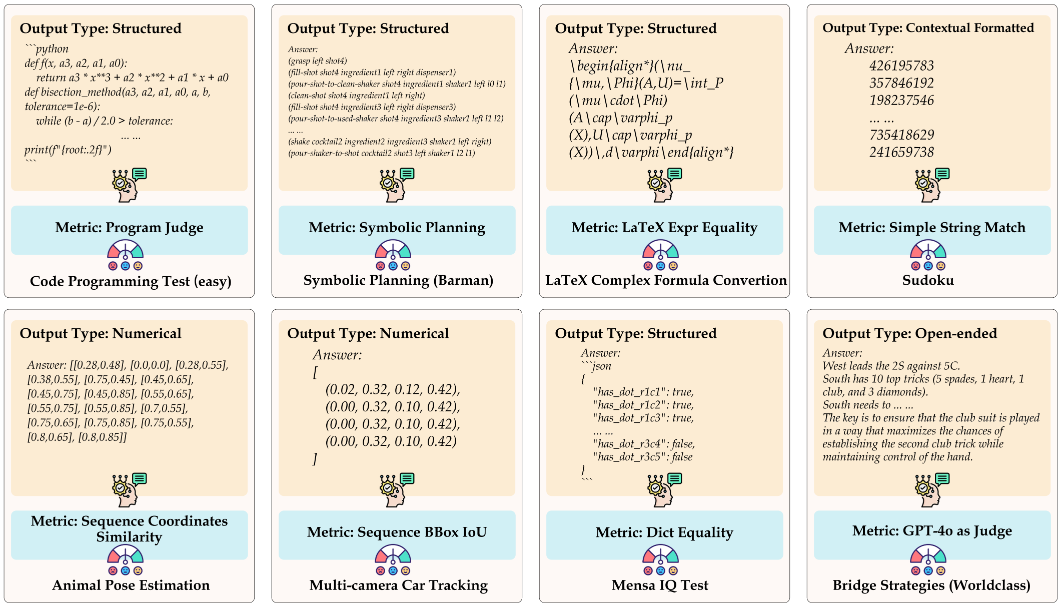
3.2 METRICS FOR ANSWERS IN DIVERSE OUTPUT FORMATS

To properly evaluate the tasks with different output formats, we develop a set of *highly-customized evaluation metrics* in parallel with the benchmark construction process (§3.1). Figure 4 shows several examples of the model outputs along with the task's associated metrics. When new tasks are submitted to our GitHub repository, we implement any new metrics specified by the task authors. We use two types of metrics: rule-based metrics and LLM-assisted metrics. All metrics are normalized into [0, 1], with 1.0 being the full mark.

Rule-based metrics. When there is a unique answer under the question context or the correctness of the answer can be verified by rules (e.g., if the generated story/poetry meets the desired formats or if the generated code can pass test cases), we implement *rule-based* metrics for evaluation. To satisfy the needs of all tasks submitted by annotators, we end up with a suite of over 40 rule-based metrics. Robust string parsing is also implemented to extract the answer from the model's response. We conduct a sanity check to ensure the correct implementation of rule-based metrics. Specifically, we create an "oracle" model that always returns the ground truth, then compute its score over all tasks evaluated by rule-based metrics. The sanity check is passed when the "oracle" model gets a full 1.0 score. See §D.4 for details.

LLM-assisted metrics. For open-ended tasks that do not have a unique answer, we instead employ an *LLM-assisted* metric (Zheng et al., 2023; Li et al., 2023a). We design a per-task evaluation prompt template and fill in the tailored evaluation criteria for each task. The LLM is instructed to compare the model response with the reference answer and assign a score from 1 to 10. The score is then normalized into [0, 1] to be consistent with the other metrics. See §D.3 for details.

We divide the tasks into two subsets based on the different evaluation processes. The *Core Set* is evaluated with rule-based metrics to make the evaluation fast and cost-free. The *Open-Ended Set* is evaluated with metrics that use an LLM-as-a-judge, where the evaluation pipeline calls a proprietary LLM over an API. Specifically, we use GPT-4o-0806 (OpenAI, 2024a) as the judge LLM while maintaining an extensible implementation for using other judge models. The Core and Open-Ended sets contain 440 and 65 tasks, respectively.



~~~~
```python
def f(x, a3, a2, a1, a0):
    return a3 * x**3 + a2 * x**2 + a1 * x + a0
def bisection_method(a3, a2, a1, a0, a, b,
tolerance=1e-6):
    while (b - a) / 2.0 > tolerance:
                        ... ...
print(f"{root:.2f}")
```
~~~~

```
Answer:
(grasp left shot4)
(fill-shot shot4 ingredient1 left right dispenser1)
(pour-shot-to-clean-shaker shot4 ingredient1 shaker1 left l0 l1)
(clean-shot shot4 ingredient1 left right)
(fill-shot shot4 ingredient3 left right dispenser3)
(pour-shot-to-used-shaker shot4 ingredient3 shaker1 left l1 l2)
... ...
(shake cocktail2 ingredient2 ingredient3 shaker1 left right)
(pour-shaker-to-shot cocktail2 shot3 left shaker1 l2 l1)
```

```
Answer:
\begin{align*}(\nu_
{\mu,\Phi}(A,U)=\int_P
(\mu\cdot\Phi)
(A\cap\varphi_p
(X),U\cap\varphi_p
(X))\,d\varphi\end{align*}
```

```
Answer:
    426195783
    357846192
    198237546
    ... ...
    735418629
    241659738
```

```
Answer: [[0.28,0.48], [0.0,0.0], [0.28,0.55],
[0.38,0.55], [0.75,0.45], [0.45,0.65],
[0.45,0.75], [0.45,0.85], [0.55,0.65],
[0.55,0.75], [0.55,0.85], [0.7,0.55],
[0.75,0.65], [0.75,0.85], [0.75,0.55],
[0.8,0.65], [0.8,0.85]]
```

```
Answer:
[
  (0.02, 0.32, 0.12, 0.42),
  (0.00, 0.32, 0.10, 0.42),
  (0.00, 0.32, 0.10, 0.42),
  (0.00, 0.32, 0.10, 0.42)
]
```

~~~~
Answer:
```json
{
  "has_dot_r1c1": true,
  "has_dot_r1c2": true,
  "has_dot_r1c3": true,
  ... ...
  "has_dot_r3c4": false,
  "has_dot_r3c5": false
}
```
~~~~

```
Answer:
West leads the 2S against 5C.
South has 10 top tricks (5 spades, 1 heart, 1
club, and 3 diamonds).
South needs to ... ...
The key is to ensure that the club suit is played
in a way that maximizes the chances of
establishing the second club trick while
maintaining control of the hand.
```

Figure 4: Representative examples of MEGA-BENCH's diverse output formats and customized metrics (input queries are omitted). The outputs are extracted from *real responses* of GPT-4o (0513). We implement robust parsing to extract the final answer from raw model responses.

3.3 MULTI-DIMENSIONAL KEYWORDS FOR FINE-GRAINED ANALYSIS

Existing multi-task multimodal benchmarks analyze models according to dimensions like the image type and academic discipline (Yue et al., 2024a), ability (Liu et al., 2023b), or meta-task (Ying et al., 2024). MEGA-BENCH offers a broad and diverse range of coverage across all these dimensions, and extends even further beyond them. As explained in §3.1, the taxonomy tree divides the tasks into general application scenarios, the most manageable dimension for distributing the annotation efforts to different annotators. After we collected all tasks and finished the quality control process, we grouped all tasks based on four extra dimensions: input visual type, input visual number, output format, and required skills (Figure 2). Each dimension has 6 to 10 keywords, enabling fine-grained analysis and comparison. Interactive visualization tools can then be developed based on our evaluation results, which allows model developers to delve deep into different aspects of a model and compare different models comprehensively.

3.4 DATASET STATISTICS AND COMPARISON WITH OTHER BENCHMARKS

MEGA-BENCH contains 505 real-world tasks with 8,186 manually annotated or repurposed samples. Even for repurposed data, considerable effort is needed to convert the original annotations into specific task descriptions, diverse output formats, and additional instructions to include auxiliary information about formatting. Figure 2 shows the task distribution of all five dimensions, and the detailed task taxonomy tree and statistics of each dimension are in Appendix C.

Table 1 compares MEGA-BENCH to existing multimodal benchmarks. The key feature of our benchmark is the diversity across all aspects, driven by our high-level designs of diverse task applications and output formats. MMMU (Yue et al., 2024a;b) focuses on college-level exam questions with various discipline and image formats. All questions are single-image and answered in multiple-choice format. MMT-Bench (Ying et al., 2024) covers 162 concrete sub-tasks, enabling in-depth analysis based on their "taskonomy" and diverse input forms. However, all of the tasks MMT-Bench are from existing datasets, mostly under the "Perception" sub-tree in our taxonomy, and all outputs are in multiple-choice form like MMMU. To maximize task coverage and the diversity in model outputs with cost-effective inference, MEGA-BENCH includes a much broader range of task types and output formats, while having fewer total samples compared to existing benchmarks.

Table 1: A comparison between MEGA-Bench and existing works. MEGA-Bench has a greater diversity in data sources, input/output format, the number of metrics, and the number of tasks.

Dataset	Annotation	Source	Input	Output	#Metrics	#Tasks
VQA-v2 (Antol et al., 2015)	New	Photo	1 Image	Phrase/Bool/Num	1	1
VizwizVQA (Gurari et al., 2018)	New	Photo	1 Image	Phrase/Bool/Num	1	1
ChartQA (Masry et al., 2022)	New	Chart	1 Image	Bool/Num	1	1
AI2D (Kembhavi et al., 2016)	New	Diagram	1 Image	Multi-choice (MC)	1	1
GeoQA (Chen et al., 2021)	New	Geometry	1 Image	Multi-choice (MC)	1	1
NLVR^2 (Suhr & Artzi, 2019)	New	Photo	2 Images	Bool	1	1
InfoVQA (Mathew et al., 2022)	New	Infographics	1 Image	Phrase/Bool/Num	1	1
DocVQA (Mathew et al., 2021)	New	Document	1 Image	Phrase/Bool/Num	1	1
OCR-VQA (Mishra et al., 2019)	New	Book covers	1 Image	Phrase	1	1
ScienceQA (Lu et al., 2022)	New	K12 Books	$\leq$1 Image	Multi-choice (MC)	1	26
MathVista (Lu et al., 2023)	Repurposed	Diverse	1 Image	MC / Num	1	5
MMBench (Liu et al., 2023b)	Hybrid	Diverse	1 Image	Multi-choice (MC)	1	20
MME (Yin et al., 2023)	Repurposed	Existing	1 Image	Multi-choice (MC)	1	14
Seed-Bench (Li et al., 2024c)	New	Existing	Image/Video	Multi-choice (MC)	1	12
VisIT-Bench (Bitton et al., 2023)	Hybrid	Diverse	1/2 Images	Free-form (FF)	1	70
MMStar (Chen et al., 2024a)	Repurposed	Existing	1 Image	Multi-choice (MC)	1	18
MM-Vet (Yu et al., 2024b)	Repurposed	Existing	1 Image	Free-form (FF)	1	16
MMMU (Yue et al., 2024a)	New	Diverse	$\geq$1 Image	MC / FF	1	30
MUIRBench (Wang et al., 2024a)	Hybrid	Existing	>1 Image	Multi-choice (MC)	1	12
MileBench (Song et al., 2024)	Repurposed	Existing	>1 Image	MC / FF	2	12
VideoMME (Fu et al., 2024a)	New	Youtube	Video	Multi-choice (MC)	1	30
MVBench (Li et al., 2024e)	Repurposed	Existing	Video	Multi-choice (MC)	1	20
MMT-Bench (Ying et al., 2024)	Repurposed	Existing	$\geq$1 Image/Video	Multi-choice (MC)	1	162
MEGA-Bench	New	Diverse	$\geq$1 Image/Video	Unrestricted	45	505

4 EXPERIMENTS

We evaluate 19 VLMs with multi-image support on MEGA-Bench. §4.1 describes the evaluated models and the evaluation pipeline. §4.2 presents the evaluation results with a fine-grained analytical breakdown. §4.3 provides analyses on the number of examples per task and error types.

4.1 EVALUATION SETTINGS

Evaluated models. We evaluate a diverse range of large multimodal models. The proprietary models assessed include GPT-4o (0513) and GPT-4o mini (OpenAI, 2024a), Claude-3.5-Sonnet (0620 and 1022) (Anthropic, 2024a;b), Gemini-1.5-Pro (002) and Gemini-1.5-Flash (002) (Google, 2024a). For open-source models, we mainly focus on large flagship (>70B parameters) and small-to-medium efficiency models. The large models include Qwen2-VL-72B (Alibaba, 2024), InternVL2-Llama3-76B (Chen et al., 2024d), LLaVA-OneVision-72B (Li et al., 2024a), and NVLM (Dai et al., 2024). The medium-scale models comprise Qwen2-VL-7B (Alibaba, 2024), Pixtral 12B (Mistral, 2024), Aria (Li et al., 2024d), InternVL2-8B (Chen et al., 2024d), Phi-3.5-Vision (Abdin et al., 2024), MiniCPM-V2.6 (Yao et al., 2024), LLaVA-OneVision-7B (Li et al., 2024a), Llama-3.2-11B Meta (2024), and Idefics3-8B-Llama3 (Laurençon et al., 2024).

Evaluation pipeline. MEGA-Bench has diverse and flexible formats. To ensure the models have clear instructions on the output format, we provide all evaluated VLMs with a one-shot in-context example. For each query, we fill in a pre-defined prompt template with the task instructions written by the task annotators, the 1-shot example, and the concrete query question. Since this one-shot example's primary purpose is to illustrate the output format, we allocate only a tiny portion of the total image budget for it. For each model, we conduct experiments with and without Chain-of-Thought (CoT) prompting (Wei et al., 2022) for the Core tasks (the one-shot example of Open-ended tasks already contains CoT demonstrations). The prompt templates and other evaluation details (e.g., the frame sampling strategy for video inputs) are in §D. Our default evaluation pipeline focuses on models with multi-image support. To properly evaluate models trained mainly for single-image use cases, we create a single-image setting using the single-image tasks of MEGA-Bench. See §A for the detailed results and analyses of the single-image setting.

Table 2: The main results of different models on the Core and Open-ended subset of MEGA-BENCH, with 440 and 65 tasks, respectively. We report the macro mean scores across all tasks in each set. The overall score is the weighted average of the Core and Open-ended scores. When computing the overall score, we use the higher Core score from 'w/o CoT' and 'w/ CoT'.

Model	Eval Tier	Open Source	**Core** (rule eval)		**Open-ended** (GPT eval)	**Overall**
			w/o CoT	w/ CoT		
Claude-3.5-Sonnet (1022) (Anthropic, 2024b)	Flagship	No	49.20	52.59	**65.63**	**54.27**
GPT-4o (0513) (OpenAI, 2024a)	Flagship	No	**52.03**	**52.65**	64.78	54.21
Claude-3.5-Sonnet (0620) (Anthropic, 2024a)	Flagship	No	48.80	50.41	63.74	52.13
Gemini-1.5-Pro-002 (Google, 2024b)	Flagship	No	46.99	48.22	58.58	49.55
Gemini-1.5-Flash-002 (Google, 2024b)	Efficiency	No	**41.90**	**41.89**	56.91	**43.82**
GPT-4o mini (OpenAI, 2024b)	Efficiency	No	39.85	40.77	**58.65**	43.07
Qwen2-VL-72B (Alibaba, 2024)	Flagship	Yes	**46.41**	**45.42**	**56.40**	**47.70**
InternVL2-Llama3-76B (Chen et al., 2024d)	Flagship	Yes	35.02	35.63	51.93	37.73
LLaVA-OneVision-72B (Li et al., 2024a)	Flagship	Yes	31.99	29.74	45.99	33.79
NVLM-72B (Dai et al., 2024)	Flagship	Yes	24.21	21.59	34.78	25.57
Qwen2-VL-7B (Alibaba, 2024)	Efficiency	Yes	**34.80**	**32.93**	43.96	**35.98**
Pixtral-12B (Mistral, 2024)	Efficiency	Yes	31.91	31.36	45.66	33.68
Aria-MoE-25B (Li et al., 2024d)	Efficiency	Yes	30.49	28.90	**51.03**	33.13
InternVL2-8B (Chen et al., 2024d)	Efficiency	Yes	25.96	24.09	39.79	27.74
Phi-3.5-Vision-4B (Abdin et al., 2024)	Efficiency	Yes	23.27	23.00	39.48	25.36
MiniCPM-V2.6-8B (Yao et al., 2024)	Efficiency	Yes	22.88	22.96	41.73	25.38
LLaVA-OneVision-7B (Li et al., 2024a)	Efficiency	Yes	22.41	21.36	33.98	23.90
Llama-3.2-11B (Meta, 2024)	Efficiency	Yes	10.04	16.00	31.73	18.02
Idefics3-8B-Llama3 (Laurençon et al., 2024)	Efficiency	Yes	11.12	8.96	32.11	13.82

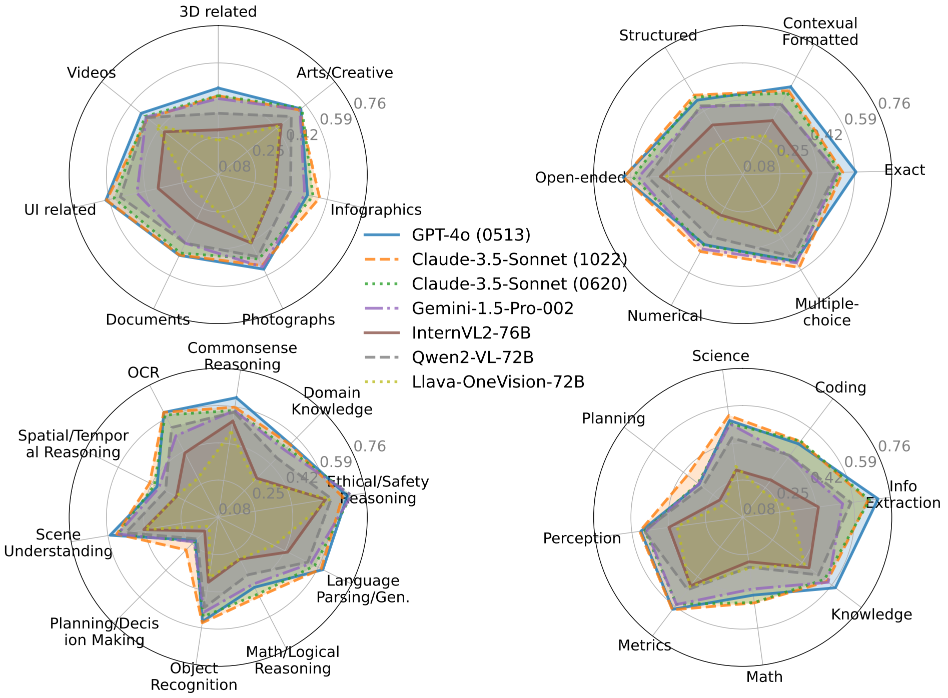


Figure 5: Fine-grained breakdown analysis of flagship models on four dimensions. From top-left to bottom-right: input format, output format, skills, and application.

4.2 MAIN RESULTS WITH BREAKDOWN ANALYSIS

Table 2 presents the main evaluation results, with Figure 5 and Figure 6 being the accompanying fine-grained breakdowns enabled by MEGA-BENCH's multi-dimensional diversity. We discuss some important findings below and leave a full breakdown of the results in §E of the Appendix.

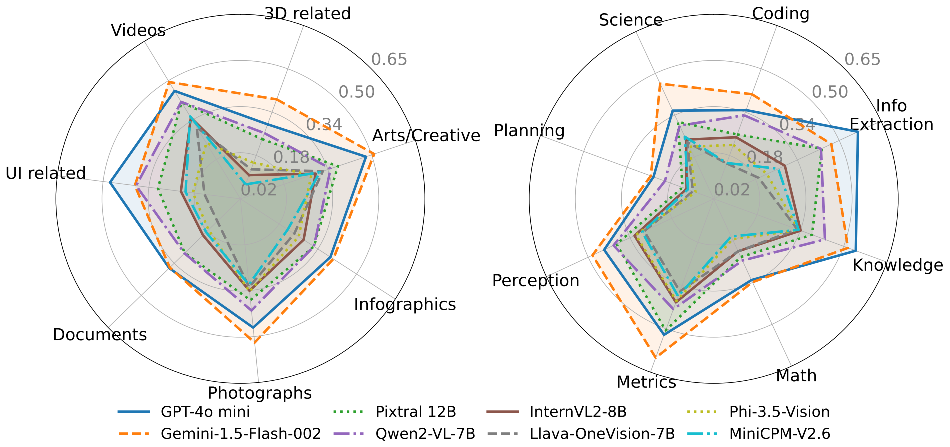


Figure 6: Fine-grained analysis of efficiency models on input format (left) and application (right).

For the sake of careful comparison, we organize the results into two tiers: (1) The *Flagship Model Tier* compares the strongest performing models from each model's organization, (believed) with #params $\geq$ 70B. (2) The *Efficiency Model Tier* compares efficiency models from each model's organization, (believed) with #params $\leq$ 20B.

Flagship models. Unlike the results on recent benchmarks like MMMU-Pro (Yue et al., 2024b) where GPT-4o (0513) and Claude-3.5-Sonnet (0620) get close scores, GPT-4o (0513) outperforms Claude-3.5-Sonnet (0620) with a clear margin on MEGA-BENCH ($> 2\%$). Investigating the breakdown results, we observe that GPT-4o (0513) wins in most applications/skills except for coding, math, and planning-related tasks, where the answers are typically in a "structured" output format (Figure 5). The recent update of Claude-3.5-Sonnet (1022) makes improvements across almost all dimensions, especially in planning tasks and those with infographics/UI/photographs inputs, and slightly surpasses GPT-4o in the overall score ($< 0.1\%$). The "planning" application keyword contains tasks like symbolic planning (Zhu et al., 2024), navigation (Ku et al., 2020), chess games (Fu et al., 2024b), puzzle games (e.g., maze, Sudoku), etc., and even the best models get low scores.

One typical observation of Claude-3.5-Sonnet models is that they tend to be meticulous and refuse to answer routine knowledge or commonsense questions, such as the name and nationality of famous actors. The bottom radar maps show that they fall behind in knowledge, information extraction, and commonsense reasoning compared to GPT-4o, partially because of this refusal behavior.

The evaluation results suggest that Qwen2-VL performs particularly well amongst open-source models of similar parameter sizes. In Figure 5, Qwen2-VL-72B gets a similar score to closed-source models in the general perception category and outperforms Gemini-1.5-Pro-002 on information extraction tasks. Llava-OneVision-72B scores very low when the visual inputs are in "UI related" and "Document" formats while performing well on video inputs. This suggests a lack of OCR and language parsing abilities, which can be confirmed with its skills radar plot.

Efficiency models. Figure 6 analyzes the results on efficiency models. In general, Gemini-1.5-flash-002 has the best performance with exceptional scores in Science and Metrics applications. The Metrics keyword contains tasks such as rating the quality of GenAI results (He et al., 2024; Jiang et al., 2024b) and requires deep multimodal reasoning and commonsense. However, its performance on UI-related inputs and information extraction tasks falls behind GPT-4o mini.

Chain-of-Thought. An interesting finding is that the CoT prompt (See §D) effectively guides all proprietary models to generate a detailed reasoning process, and flagship-tier proprietary models all obtain better performance on the Core set. However, it has almost no effect on most open-source models. For example, the Qwen2-VL, InternVL2, and LLaVA-OneVision models rarely produce reasoning when given a CoT instruction, and sometimes get confused about the required format after generating the reasoning process, leading to a lower score on the Core set.

Some open-source models get comparatively low scores for their parameter count. Llama-3.2-11B has difficulty leveraging the one-shot example to understand the correct output format and tends to

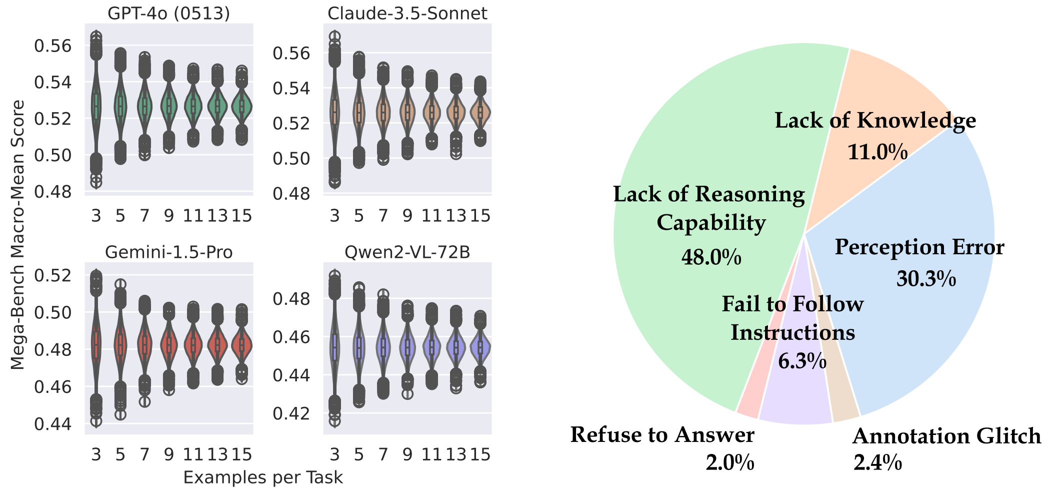


Figure 7: (Left) The bootstrap distribution of benchmark scores (w/ CoT prompting) with a gradually increased bootstrap sample size of the number of per-task examples. (Right) The task-wise error distribution of GPT-4o (0513) over a subset of 255 Core tasks.

generate a long descriptive sentence instead. This issue is alleviated under the CoT setting because the prompt provides extra instructions on the output format beyond the one-shot example, requesting the model to strictly separate the reasoning process from the final answer. Idefics3 frequently repeats the example answer from the one-shot demonstration. We suspect the reason for this problem is the poor support for multi-image (as our query contains at least two images, including the one-shot example) since it can generate reasonable responses with a single-image input. §A in the Appendix presents a single-image setting of MEGA-BENCH and conducts further analyses.

4.3 MORE ANALYSIS

Number of samples per task. As discussed in §1, one of MEGA-BENCH's goals is to optimize the inference cost while still producing detailed multi-dimensional breakdown analysis. Therefore, we prioritize expanding the number of tasks over adding many examples per task in the benchmark construction process. To understand the robustness of the benchmark score with around 15 examples per task, we obtained bootstrap distributions (Efron & Tibshirani, 1994; Hesterberg, 2011) of the model scores for our Core set with the CoT prompting. We did this by taking a random subset of the model's responses of size n ($n = 3, 5, \ldots, 13, 15$) with replacement for each task and calculating the task-level macro-mean scores. To ensure the bootstrap distribution was numerically stable, we ran 10,000 Monte Carlo simulations. Figure 7 (left) shows that the variance in model scores rapidly narrows as the number of examples per task increases. As the number of examples per task increases beyond 7, the marginal return in variance reduction diminishes.

Error analysis. To understand the limitations of state-of-the-art VLMs, we analyze the GPT-4o (0513) results by manually identifying the error types over a subset of 255 tasks from the Core set. We use the CoT setting since the reasoning process helps determine the error type. Figure 7 (right) presents the error distribution. For GPT-4o, the lack of various reasoning capabilities (e.g., symbolic reasoning for planning/coding tasks, spatial or temporal reasoning for complex perception tasks, etc.) is the dominating failure mode on MEGA-BENCH. Please refer to §F for the full definition of error types and detailed example-wise inspection results with different models.

5 CONCLUSION

This paper presents MEGA-BENCH, a comprehensive benchmark that scales multimodal evaluation to over 500 real-world tasks but at a manageable inference cost. By systematically organizing tasks across dimensions like skill, output format, and input type, we enable fine-grained analysis of multimodal models. Our evaluation of state-of-the-art VLMs revealed significant performance variations between models that previously seemed similar. MEGA-BENCH provides a new standard for multimodal evaluation, offering a robust analysis tool for model development.

REFERENCES

Marah Abdin, Sam Ade Jacobs, Ammar Ahmad Awan, Jyoti Aneja, Ahmed Awadallah, Hany Awadalla, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Harkirat Behl, et al. Phi-3 technical report: A highly capable language model locally on your phone. ArXiv preprint, abs/2404.14219, 2024. URL `https://arxiv.org/abs/2404.14219`.

Alibaba. Qwen2-vl: To see the world more clearly. https://qwenlm.github.io/blog/qwen2-vl/ , 2024.

Norah Alzahrani, Hisham Alyahya, Yazeed Alnumay, Sultan AlRashed, Shaykhah Alsubaie, Yousef Almushayqih, Faisal Mirza, Nouf Alotaibi, Nora Al-Twairesh, Areeb Alowisheq, M Saiful Bari, and Haidar Khan. When benchmarks are targets: Revealing the sensitivity of large language model leaderboards. In Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 13787–13805. Association for Computational Linguistics, August 2024.

Anthropic. Claude 3.5 sonnet. https://www.anthropic.com/news/claude-3-5-sonnet, 2024a. URL `https://www.anthropic.com/news/claude-3-5-sonnet`.

Anthropic. Introducing computer use, a new claude 3.5 sonnet, and claude 3.5 haiku, 2024b. URL `https://www.anthropic.com/news/3-5-models-and-computer-use`.

Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. VQA: visual question answering. In 2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015, pp. 2425–2433. IEEE Computer Society, 2015. doi: 10.1109/ICCV.2015.279. URL `https://doi.org/10.1109/ICCV.2015.279`.

Sherwin Bahmani, Ivan Skorokhodov, Aliaksandr Siarohin, Willi Menapace, Guocheng Qian, Michael Vasilkovsky, Hsin-Ying Lee, Chaoyang Wang, Jiaxu Zou, Andrea Tagliasacchi, et al. Vd3d: Taming large video diffusion transformers for 3d camera control. arXiv preprint arXiv:2407.12781, 2024.

Yuelin Bai, Xinrun Du, Yiming Liang, Yonggang Jin, Ziqiang Liu, Junting Zhou, Tianyu Zheng, Xincheng Zhang, Nuo Ma, Zekun Wang, et al. Coig-cqia: Quality is all you need for chinese instruction fine-tuning, 2024.

Yonatan Bitton, Hritik Bansal, Jack Hessel, Rulin Shao, Wanrong Zhu, Anas Awadalla, Josh Gardner, Rohan Taori, and Ludwig Schimdt. Visit-bench: A benchmark for vision-language instruction following inspired by real-world use. arXiv preprint arXiv:2308.06595, 2023.

Holger Caesar, Varun Bankiti, Alex H Lang, Sourabh Vora, Venice Erin Liong, Qiang Xu, Anush Krishnan, Yu Pan, Giancarlo Baldan, and Oscar Beijbom. nuscenes: A multimodal dataset for autonomous driving. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 11621–11631, 2020.

Shuaichen Chang, David Palzer, Jialin Li, Eric Fosler-Lussier, and Ningchuan Xiao. Mapqa: A dataset for question answering on choropleth maps. arXiv preprint arXiv:2211.08545, 2022.

Ting-Yun Chang and Robin Jia. Data curation alone can stabilize in-context learning. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 8123–8144. Association for Computational Linguistics, July 2023.

Jiaqi Chen, Jianheng Tang, Jinghui Qin, Xiaodan Liang, Lingbo Liu, Eric P Xing, and Liang Lin. Geoqa: A geometric question answering benchmark towards multimodal numerical reasoning. arXiv preprint arXiv:2105.14517, 2021.

Lin Chen, Jinsong Li, Xiaoyi Dong, Pan Zhang, Yuhang Zang, Zehui Chen, Haodong Duan, Jiaqi Wang, Yu Qiao, Dahua Lin, et al. Are we on the right way for evaluating large vision-language models? arXiv preprint arXiv:2403.20330, 2024a.

Pengcheng Chen, Jin Ye, Guoan Wang, Yanjun Li, Zhongying Deng, Wei Li, Tianbin Li, Haodong Duan, Ziyan Huang, Yanzhou Su, et al. Gmai-mmbench: A comprehensive multimodal evaluation benchmark towards general medical ai. arXiv preprint arXiv:2408.03361, 2024b.

Wenhu Chen, Hongmin Wang, Jianshu Chen, Yunkai Zhang, Hong Wang, Shiyang Li, Xiyou Zhou, and William Yang Wang. Tabfact: A large-scale dataset for table-based fact verification. arXiv preprint arXiv:1909.02164, 2019.

Wentong Chen, Junbo Cui, Jinyi Hu, Yujia Qin, Junjie Fang, Yue Zhao, Chongyi Wang, Jun Liu, Guirong Chen, Yupeng Huo, Yuan Yao, Yankai Lin, Zhiyuan Liu, and Maosong Sun. Guicourse: From general vision language models to versatile gui agents, 2024c.

Zhe Chen, Weiyun Wang, Hao Tian, Shenglong Ye, Zhangwei Gao, Erfei Cui, Wenwen Tong, Kongzhi Hu, Jiapeng Luo, Zheng Ma, et al. How far are we to gpt-4v? closing the gap to commercial multimodal models with open-source suites. ArXiv preprint, abs/2404.16821, 2024d. URL `https://arxiv.org/abs/2404.16821`.

Wei-Lin Chiang, Lianmin Zheng, Ying Sheng, Anastasios Nikolas Angelopoulos, Tianle Li, Dacheng Li, Hao Zhang, Banghua Zhu, Michael Jordan, Joseph E. Gonzalez, and Ion Stoica. Chatbot arena: An open platform for evaluating llms by human preference, 2024.

Tai-Yin Chiu, Yinan Zhao, and Danna Gurari. Assessing image quality issues for real-world problems. In proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020.

François Chollet. On the measure of intelligence, 2019. URL `https://arxiv.org/abs/1911.01547`.

Wenliang Dai, Nayeon Lee, Boxin Wang, Zhuolin Yang, Zihan Liu, Jon Barker, Tuomas Rintamaki, Mohammad Shoeybi, Bryan Catanzaro, and Wei Ping. Nvlm: Open frontier-class multimodal llms. arXiv preprint, 2024.

Dima Damen, Hazel Doughty, Giovanni Maria Farinella, Sanja Fidler, Antonino Furnari, Evangelos Kazakos, Davide Moltisanti, Jonathan Munro, Toby Perrett, Will Price, et al. Scaling egocentric vision: The epic-kitchens dataset. In Proceedings of the European conference on computer vision (ECCV), pp. 720–736, 2018.

Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José MF Moura, Devi Parikh, and Dhruv Batra. Visual dialog. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 326–335, 2017.

Rocktim Jyoti Das, Simeon Emilov Hristov, Haonan Li, Dimitar Iliyanov Dimitrov, Ivan Koychev, and Preslav Nakov. Exams-v: A multi-discipline multilingual multimodal exam benchmark for evaluating vision language models. arXiv preprint arXiv:2403.10378, 2024.

Matt Deitke, Christopher Clark, Sangho Lee, Rohun Tripathi, Yue Yang, Jae Sung Park, Mohammadreza Salehi, Niklas Muennighoff, Kyle Lo, Luca Soldaini, et al. Molmo and pixmo: Open weights and open data for state-of-the-art multimodal models. arXiv preprint arXiv:2409.17146, 2024.

Li Deng. The mnist database of handwritten digit images for machine learning research, 2012.

Bradley Efron and Robert J Tibshirani. An introduction to the bootstrap. Chapman and Hall/CRC, 1994.

Yue Fan, Jing Gu, Kaiwen Zhou, Qianqi Yan, Shan Jiang, Ching-Chen Kuo, Xinze Guan, and Xin Eric Wang. Muffin or chihuahua? challenging large vision-language models with multipanel vqa. arXiv preprint arXiv:2401.15847, 2024.

Chaoyou Fu, Yuhan Dai, Yondong Luo, Lei Li, Shuhuai Ren, Renrui Zhang, Zihan Wang, Chenyu Zhou, Yunhang Shen, Mengdan Zhang, et al. Video-mme: The first-ever comprehensive evaluation benchmark of multi-modal llms in video analysis. arXiv preprint arXiv:2405.21075, 2024a.

Deqing Fu, Ruohao Guo, Ghazal Khalighinejad, Ollie Liu, Bhuwan Dhingra, Dani Yogatama, Robin Jia, and Willie Neiswanger. IsoBench: Benchmarking multimodal foundation models on isomorphic representations. In First Conference on Language Modeling (COLM), 2024b. First four authors contributed equally.

Xingyu Fu, Yushi Hu, Bangzheng Li, Yu Feng, Haoyu Wang, Xudong Lin, Dan Roth, Noah A Smith, Wei-Chiu Ma, and Ranjay Krishna. Blink: Multimodal large language models can see but not perceive. ArXiv preprint, abs/2404.12390, 2024c. URL https://arxiv.org/abs/2404.12390.

Daniel Geng and Andrew Owens. Motion guidance: Diffusion-based image editing with differentiable motion estimators. arXiv preprint arXiv:2401.18085, 2024.

Zahra Gharaee, ZeMing Gong, Nicholas Pellegrino, Iuliia Zarubiieva, Joakim Bruslund Haurum, Scott Lowe, Jaclyn McKeown, Chris Ho, Joschka McLeod, Yi-Yun Wei, et al. A step towards worldwide biodiversity assessment: The bioscan-1m insect dataset. Advances in Neural Information Processing Systems, 36, 2024.

Google. Gemini: a family of highly capable multimodal models. ArXiv preprint, abs/2312.11805, 2023. URL https://arxiv.org/abs/2312.11805.

Google. Updated production-ready gemini models, reduced 1.5 pro pricing, increased rate limits, and more. https://developers.googleblog.com/en/updated-production-ready-gemini-models-reduced-15-pro-pricing-increased-rate-limits-and-more/, 2024a. URL https://developers.googleblog.com/en/updated-production-ready-gemini-models-reduced-15-pro-pricing-increased-rate-limits-and-more/.

Google. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. ArXiv preprint, abs/2403.05530, 2024b. URL https://arxiv.org/abs/2403.05530.

Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the V in VQA matter: Elevating the role of image understanding in visual question answering. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pp. 6325–6334. IEEE Computer Society, 2017. doi: 10.1109/CVPR.2017.670. URL https://doi.org/10.1109/CVPR.2017.670.

Shuhao Gu, Jialing Zhang, Siyuan Zhou, Kevin Yu, Zhaohu Xing, Liangdong Wang, Zhou Cao, Jintao Jia, Zhuoyi Zhang, Yixuan Wang, et al. Infinity-mm: Scaling multimodal performance with large-scale and high-quality instruction data. arXiv preprint arXiv:2410.18558, 2024.

Haisu Guan, Huanxin Yang, Xinyu Wang, Shengwei Han, Yongge Liu, Lianwen Jin, Xiang Bai, and Yuliang Liu. Deciphering oracle bone language with diffusion models, 2024. URL https://arxiv.org/abs/2406.00684.

Danna Gurari, Qing Li, Abigale J Stangl, Anhong Guo, Chi Lin, Kristen Grauman, Jiebo Luo, and Jeffrey P Bigham. Vizwiz grand challenge: Answering visual questions from blind people. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 3608–3617, 2018.

Xuan He, Dongfu Jiang, Ge Zhang, Max W.F. Ku, Achint Soni, Sherman Siu, Haonan Chen, Abhranil Chandra, Ziyan Jiang, Aaran Arulraj, Kai Wang, Quy Duc Do, Yuansheng Ni, Bohan Lyu, Yaswanth Narsupalli, Rongqi Fan, Zhiheng Lyu, Yuchen Lin, and Wenhu Chen. Videoscore: Building automatic metrics to simulate fine-grained human feedback for video generation. ArXiv, abs/2406.15252, 2024. URL https://api.semanticscholar.org/CorpusID:270688037.

Lukas Helff, Felix Friedrich, Manuel Brack, Kristian Kersting, and Patrick Schramowski. Llavaguard: Vlm-based safeguards for vision dataset curation and safety assessment. arXiv preprint arXiv:2406.05113, 2024.

Jack Hessel, Ana Marasović, Jena D Hwang, Lillian Lee, Jeff Da, Rowan Zellers, Robert Mankoff, and Yejin Choi. Do androids laugh at electric sheep? humor" understanding" benchmarks from the new yorker caption contest. arXiv preprint arXiv:2209.06293, 2022.

Tim Hesterberg. Bootstrap. Wiley Interdisciplinary Reviews: Computational Statistics, 3(6):497–526, 2011.

Xin Hong, Yanyan Lan, Liang Pang, Jiafeng Guo, and Xueqi Cheng. Visual reasoning: From state to transformation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(9):11352–11364, 2023.

Hexiang Hu, Yi Luan, Yang Chen, Urvashi Khandelwal, Mandar Joshi, Kenton Lee, Kristina Toutanova, and Ming-Wei Chang. Open-domain visual entity recognition: Towards recognizing millions of wikipedia entities. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 12065–12075, 2023.

Drew A. Hudson and Christopher D. Manning. GQA: A new dataset for real-world visual reasoning and compositional question answering. In IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019, pp. 6700–6709. Computer Vision Foundation / IEEE, 2019. doi: 10.1109/CVPR.2019.00686.

HuggingFaceM4. Docmatix dataset, 2024. URL `https://huggingface.co/datasets/HuggingFaceM4/Docmatix`.

Naman Jain, King Han, Alex Gu, Wen-Ding Li, Fanjia Yan, Tianjun Zhang, Sida Wang, Armando Solar-Lezama, Koushik Sen, and Ion Stoica. Livecodebench: Holistic and contamination free evaluation of large language models for code, 2024a. URL `https://arxiv.org/abs/2403.07974`.

Neel Jain, Ping yeh Chiang, Yuxin Wen, John Kirchenbauer, Hong-Min Chu, Gowthami Somepalli, Brian R. Bartoldson, Bhavya Kailkhura, Avi Schwarzschild, Aniruddha Saha, Micah Goldblum, Jonas Geiping, and Tom Goldstein. NEFTune: Noisy embeddings improve instruction finetuning. In The Twelfth International Conference on Learning Representations, 2024b.

Guillaume Jaume, Hazim Kemal Ekenel, and Jean-Philippe Thiran. Funsd: A dataset for form understanding in noisy scanned documents. In 2019 International Conference on Document Analysis and Recognition Workshops (ICDARW), volume 2, pp. 1–6. IEEE, 2019.

Dongfu Jiang, Xuan He, Huaye Zeng, Cong Wei, Max Ku, Qian Liu, and Wenhu Chen. Mantis: Interleaved multi-image instruction tuning. ArXiv preprint, abs/2405.01483, 2024a. URL `https://arxiv.org/abs/2405.01483`.

Dongfu Jiang, Max Ku, Tianle Li, Yuansheng Ni, Shizhuo Sun, Rongqi Fan, and Wenhu Chen. Genai arena: An open evaluation platform for generative models. arXiv preprint arXiv:2406.04485, 2024b.

Yiqiao Jin, Minje Choi, Gaurav Verma, Jindong Wang, and Srijan Kumar. Mm-soc: Benchmarking multimodal large language models in social media platforms. ArXiv preprint, abs/2402.14154, 2024. URL `https://arxiv.org/abs/2402.14154`.

Justin Johnson, Bharath Hariharan, Laurens Van Der Maaten, Li Fei-Fei, C Lawrence Zitnick, and Ross Girshick. Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2901–2910, 2017.

Kushal Kafle, Brian Price, Scott Cohen, and Christopher Kanan. Dvqa: Understanding data visualizations via question answering. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 5648–5656, 2018.

Samira Ebrahimi Kahou, Vincent Michalski, Adam Atkinson, Ákos Kádár, Adam Trischler, and Yoshua Bengio. Figureqa: An annotated figure dataset for visual reasoning. arXiv preprint arXiv:1710.07300, 2017.

Aniruddha Kembhavi, Mike Salvato, Eric Kolve, Minjoon Seo, Hannaneh Hajishirzi, and Ali Farhadi. A diagram is worth a dozen images. In Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14, pp. 235–251. Springer, 2016.

Mohammad Abdullah Matin Khan, M Saiful Bari, Xuan Long Do, Weishi Wang, Md Rizwan Parvez, and Shafiq Joty. xcodeeval: A large scale multilingual multitask benchmark for code understanding, generation, translation and retrieval, 2023. URL https://arxiv.org/abs/2303.03004.

Jing Yu Koh, Robert Lo, Lawrence Jang, Vikram Duvvur, Ming Lim, Po-Yu Huang, Graham Neubig, Shuyan Zhou, Russ Salakhutdinov, and Daniel Fried. VisualWebArena: Evaluating multimodal agents on realistic visual web tasks. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 881–905, Bangkok, Thailand, 2024. Association for Computational Linguistics. URL https://aclanthology.org/2024.acl-long.50.

Jacob Krantz, Erik Wijmans, Arjun Majumdar, Dhruv Batra, and Stefan Lee. Beyond the nav-graph: Vision-and-language navigation in continuous environments, 2020. URL https://arxiv.org/abs/2004.02857.

Alexander Ku, Peter Anderson, Roma Patel, Eugene Ie, and Jason Baldridge. Room-Across-Room: Multilingual vision-and-language navigation with dense spatiotemporal grounding. In Conference on Empirical Methods for Natural Language Processing (EMNLP), 2020.

Max Ku, Tianle Li, Kai Zhang, Yujie Lu, Xingyu Fu, Wenwen Zhuang, and Wenhu Chen. Imagenhub: Standardizing the evaluation of conditional image generation models. arXiv preprint arXiv:2310.01596, 2023.

Max Ku, Dongfu Jiang, Cong Wei, Xiang Yue, and Wenhu Chen. VIEScore: Towards explainable metrics for conditional image synthesis evaluation. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 12268–12290, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.663. URL https://aclanthology.org/2024.acl-long.663.

Guokun Lai, Wei-Cheng Chang, Yiming Yang, and Hanxiao Liu. Modeling long-and short-term temporal patterns with deep neural networks. In The 41st international ACM SIGIR conference on research & development in information retrieval, pp. 95–104, 2018.

Hugo Laurençon, Andrés Marafioti, Victor Sanh, and Léo Tronchon. Building and better understanding vision-language models: insights and future directions. ArXiv preprint, abs/2408.12637, 2024. URL https://arxiv.org/abs/2408.12637.

Benjamin Charles Germain Lee, Jaime Mears, Eileen Jakeway, Meghan Ferriter, Chris Adams, Nathan Yarasavage, Deborah Thomas, Kate Zwaard, and Daniel S Weld. The newspaper navigator dataset: Extracting headlines and visual content from 16 million historic newspaper pages in chronicling america. In Proceedings of the 29th ACM international conference on information & knowledge management, pp. 3055–3062, 2020.

Jiyoung Lee, Seungryong Kim, Sunok Kim, Jungin Park, and Kwanghoon Sohn. Context-aware emotion recognition networks. In Proceedings of the IEEE/CVF international conference on computer vision, pp. 10143–10152, 2019.

Bo Li, Yuanhan Zhang, Dong Guo, Renrui Zhang, Feng Li, Hao Zhang, Kaichen Zhang, Yanwei Li, Ziwei Liu, and Chunyuan Li. Llava-onevision: Easy visual task transfer. ArXiv preprint, abs/2408.03326, 2024a. URL https://arxiv.org/abs/2408.03326.

Bohao Li, Yuying Ge, Yi Chen, Yixiao Ge, Ruimao Zhang, and Ying Shan. Seed-bench-2-plus: Benchmarking multimodal large language models with text-rich visual comprehension, 2024b. URL https://arxiv.org/abs/2404.16790.

Bohao Li, Yuying Ge, Yixiao Ge, Guangzhi Wang, Rui Wang, Ruimao Zhang, and Ying Shan. Seed-bench: Benchmarking multimodal large language models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 13299–13308, 2024c.

Dongxu Li, Yudong Liu, Haoning Wu, Yue Wang, Zhiqi Shen, Bowen Qu, Xinyao Niu, Guoyin Wang, Bei Chen, and Junnan Li. Aria: An open multimodal native mixture-of-experts model. arXiv preprint arXiv:2410.05993, 2024d.

Kunchang Li, Yali Wang, Yinan He, Yizhuo Li, Yi Wang, Yi Liu, Zun Wang, Jilan Xu, Guo Chen, Ping Luo, et al. Mvbench: A comprehensive multi-modal video understanding benchmark. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 22195–22206, 2024e.

Mukai Li, Lei Li, Yuwei Yin, Masood Ahmed, Zhenguang Liu, and Qi Liu. Red teaming visual language models. arXiv preprint arXiv:2401.12915, 2024f.

Xuechen Li, Tianyi Zhang, Yann Dubois, Rohan Taori, Ishaan Gulrajani, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Alpacaeval: An automatic evaluator of instruction-following models. https://github.com/tatsu-lab/alpaca_eval, 5 2023a.

Zhuowan Li, Xingrui Wang, Elias Stengel-Eskin, Adam Kortylewski, Wufei Ma, Benjamin Van Durme, and Alan L Yuille. Super-clevr: A virtual benchmark to diagnose domain robustness in visual reasoning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 14963–14973, 2023b.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13, pp. 740–755. Springer, 2014.

Junpeng Liu, Yifan Song, Bill Yuchen Lin, Wai Lam, Graham Neubig, Yuanzhi Li, and Xiang Yue. Visualwebbench: How far have multimodal llms evolved in web page understanding and grounding? Conference on Language Modeling, 2024a.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. ACM Comput. Surv., 55(9), January 2023a. ISSN 0360-0300. doi: 10.1145/3560815. URL https://doi.org/10.1145/3560815.

Yuan Liu, Haodong Duan, Yuanhan Zhang, Bo Li, Songyang Zhang, Wangbo Zhao, Yike Yuan, Jiaqi Wang, Conghui He, Ziwei Liu, et al. Mmbench: Is your multi-modal model an all-around player? ArXiv preprint, abs/2307.06281, 2023b. URL https://arxiv.org/abs/2307.06281.

Yuan Liu, Zhongyin Zhao, Ziyuan Zhuang, Le Tian, Xiao Zhou, and Jie Zhou. Points: Improving your vision-language model with affordable strategies. arXiv preprint arXiv:2409.04828, 2024b.

Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep learning face attributes in the wild. In Proceedings of the IEEE international conference on computer vision, pp. 3730–3738, 2015.

Pan Lu, Liang Qiu, Jiaqi Chen, Tony Xia, Yizhou Zhao, Wei Zhang, Zhou Yu, Xiaodan Liang, and Song-Chun Zhu. Iconqa: A new benchmark for abstract diagram understanding and visual language reasoning. arXiv preprint arXiv:2110.13214, 2021.

Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. Learn to explain: Multimodal reasoning via thought chains for science question answering. Advances in Neural Information Processing Systems, 35:2507–2521, 2022.

Pan Lu, Hritik Bansal, Tony Xia, Jiacheng Liu, Chunyuan Li, Hannaneh Hajishirzi, Hao Cheng, Kai-Wei Chang, Michel Galley, and Jianfeng Gao. Mathvista: Evaluating mathematical reasoning of foundation models in visual contexts. ArXiv preprint, abs/2310.02255, 2023. URL https://arxiv.org/abs/2310.02255.

Yujie Lu, Dongfu Jiang, Wenhu Chen, William Wang, Yejin Choi, and Bill Yuchen Lin. Wildvision arena: Benchmarking multimodal llms in the wild, February 2024. URL https://huggingface.co/spaces/WildVision/vision-arena/.

Muhammad Maaz, Hanoona Rasheed, Salman Khan, and Fahad Shahbaz Khan. Video-chatgpt: Towards detailed video understanding via large vision and language models. arXiv:2306.05424, 2023.

Xiaofeng Mao, Yuefeng Chen, Yao Zhu, Da Chen, Hang Su, Rong Zhang, and Hui Xue. Coco-o: A benchmark for object detectors under natural distribution shifts. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 6339–6350, 2023.

U-V Marti and Horst Bunke. A full english sentence database for off-line handwriting recognition. In Proceedings of the Fifth International Conference on Document Analysis and Recognition. ICDAR'99 (Cat. No. PR00318), pp. 705–708. IEEE, 1999.

Ahmed Masry, Do Xuan Long, Jia Qing Tan, Shafiq Joty, and Enamul Hoque. Chartqa: A benchmark for question answering about charts with visual and logical reasoning. arXiv preprint arXiv:2203.10244, 2022.

Minesh Mathew, Dimosthenis Karatzas, and CV Jawahar. Docvqa: A dataset for vqa on document images. In Proceedings of the IEEE/CVF winter conference on applications of computer vision, 2021.

Minesh Mathew, Viraj Bagal, Rubèn Tito, Dimosthenis Karatzas, Ernest Valveny, and CV Jawahar. Infographicvqa. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2022.

Meta. Llama 3.2: Revolutionizing edge ai and vision with open, customizable models. https://ai.meta.com/blog/llama-3-2-connect-2024-vision-edge-mobile-devices/, 2024. URL https://ai.meta.com/blog/llama-3-2-connect-2024-vision-edge-mobile-devices/.

Anand Mishra, Shashank Shekhar, Ajeet Kumar Singh, and Anirban Chakraborty. Ocr-vqa: Visual question answering by reading text in images. In 2019 international conference on document analysis and recognition (ICDAR), pp. 947–952. IEEE, 2019.

Mistral. Announcing pixtral 12b. https://mistral.ai/news/pixtral-12b/, 2024. URL https://mistral.ai/news/pixtral-12b/.

Linyong Nan, Chiachun Hsieh, Ziming Mao, Xi Victoria Lin, Neha Verma, Rui Zhang, Wojciech Kryściński, Hailey Schoelkopf, Riley Kong, Xiangru Tang, et al. Fetaqa: Free-form table question answering. Transactions of the Association for Computational Linguistics, 2022.

Teng Niu, Shiai Zhu, Lei Pang, and Abdulmotaleb El-Saddik. Sentiment analysis on multi-view social data. In MultiMedia Modeling, pp. 15–27, 2016.

Yasumasa Onoe, Sunayana Rane, Zachary Berger, Yonatan Bitton, Jaemin Cho, Roopal Garg, Alexander Ku, Zarana Parekh, Jordi Pont-Tuset, Garrett Tanzer, et al. Docci: Descriptions of connected and contrasting images. arXiv preprint arXiv:2404.19753, 2024.

OpenAI. Gpt-4v(ision) system card, 2023. URL https://cdn.openai.com/papers/GPTV_System_Card.pdf.

OpenAI. Hello gpt4-o. https://openai.com/index/hello-gpt-4o/, 2024a. URL https://openai.com/index/hello-gpt-4o/.

OpenAI. Gpt-4o mini: advancing cost-efficient intelligence. https://openai.com/index/gpt-4o-mini-advancing-cost-efficient-intelligence/, 2024b. URL https://openai.com/index/gpt-4o-mini-advancing-cost-efficient-intelligence/.

Piotr Padlewski, Max Bain, Matthew Henderson, Zhongkai Zhu, Nishant Relan, Hai Pham, Donovan Ong, Kaloyan Aleksiev, Aitor Ormazabal, Samuel Phua, et al. Vibe-eval: A hard evaluation suite for measuring progress of multimodal language models. arXiv preprint arXiv:2405.02287, 2024.

Panupong Pasupat and Percy Liang. Compositional semantic parsing on semi-structured tables. arXiv preprint arXiv:1508.00305, 2015.

Viorica Patraucean, Lucas Smaira, Ankush Gupta, Adria Recasens, Larisa Markeeva, Dylan Banarse, Skanda Koppula, Mateusz Malinowski, Yi Yang, Carl Doersch, et al. Perception test: A diagnostic benchmark for multimodal video models. Advances in Neural Information Processing Systems, 36, 2024.

Obioma Pelka, Sven Koitka, Johannes Rückert, Felix Nensa, and Christoph M Friedrich. Radiology objects in context (roco): a multimodal image dataset. In Intravascular Imaging and Computer Assisted Stenting and Large-Scale Annotation of Biomedical Data and Expert Label Synthesis: 7th Joint International Workshop, CVII-STENT 2018 and Third International Workshop, LABELS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 16, 2018, Proceedings 3, pp. 180–189. Springer, 2018.

Sai Raj Kishore Perla, Yizhi Wang, Ali Mahdavi-Amiri, and Hao Zhang. Easi-tex: Edge-aware mesh texturing from single image. ACM Trans. Graph., 2024.

Zeju Qiu, Weiyang Liu, Haiwen Feng, Zhen Liu, Tim Z. Xiao, Katherine M. Collins, Joshua B. Tenenbaum, Adrian Weller, Michael J. Black, and Bernhard Schölkopf. Can large language models understand symbolic graphics programs?, 2024. URL https://arxiv.org/abs/2408.08313.

Pooyan Rahmanzadehgervi, Logan Bolton, Mohammad Reza Taesiri, and Anh Totti Nguyen. Vision language models are blind. arXiv preprint arXiv:2407.06581, 2024.

Jonathan Roberts, Kai Han, and Samuel Albanie. Satin: A multi-task metadataset for classifying satellite imagery using vision-language models. arXiv preprint arXiv:2304.11619, 2023.

Joshua Robinson, Christopher Michael Rytting, and David Wingate. Leveraging large language models for multiple choice question answering. In The Eleventh International Conference on Learning Representations, 2023.

Stefan Romberg, Lluis Garcia Pueyo, Rainer Lienhart, and Roelof Van Zwol. Scalable logo recognition in real-world images. In Proceedings of the 1st ACM international conference on multimedia retrieval, pp. 1–8, 2011.

David Romero, Chenyang Lyu, Haryo Akbarianto Wibowo, Teresa Lynn, Injy Hamed, Aditya Nanda Kishore, Aishik Mandal, Alina Dragonetti, Artem Abzaliev, Atnafu Lambebo Tonja, et al. Cvqa: Culturally-diverse multilingual visual question answering benchmark. arXiv preprint arXiv:2406.05967, 2024.

Melanie Sclar, Yejin Choi, Yulia Tsvetkov, and Alane Suhr. Quantifying language models' sensitivity to spurious features in prompt design or: How i learned to start worrying about prompt formatting. In The Twelfth International Conference on Learning Representations, 2024.

Silvia Sellán, Yun-Chun Chen, Ziyi Wu, Animesh Garg, and Alec Jacobson. Breaking bad: A dataset for geometric fracture and reassembly. Advances in Neural Information Processing Systems, 35: 38885–38898, 2022.

Xindi Shang, Donglin Di, Junbin Xiao, Yu Cao, Xun Yang, and Tat-Seng Chua. Annotating objects and relations in user-generated videos. In Proceedings of the 2019 on International Conference on Multimedia Retrieval, pp. 279–287. ACM, 2019.

Zehong Shen, Huaijin Pi, Yan Xia, Zhi Cen, Sida Peng, Zechen Hu, Hujun Bao, Ruizhen Hu, and Xiaowei Zhou. World-grounded human motion recovery via gravity-view coordinates. arXiv preprint arXiv:2409.06662, 2024.

Haojun Shi, Suyu Ye, Xinyu Fang, Chuanyang Jin, Layla Isik, Yen-Ling Kuo, and Tianmin Shu. Muma-tom: Multi-modal multi-agent theory of mind, 2024. URL https://arxiv.org/abs/2408.12574.

Dingjie Song, Shunian Chen, Guiming Hardy Chen, Fei Yu, Xiang Wan, and Benyou Wang. Milebench: Benchmarking mllms in long context. arXiv preprint arXiv:2404.18532, 2024.

Khurram Soomro, Amir Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. ArXiv, abs/1212.0402, 2012.

Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. arXiv preprint arXiv:2206.04615, 2022.

Alane Suhr and Yoav Artzi. Nlvr2 visual bias analysis. arXiv preprint arXiv:1909.10411, 2019.

Alane Suhr, Stephanie Zhou, Ally Zhang, Iris Zhang, Huajun Bai, and Yoav Artzi. A corpus for reasoning about natural language grounded in photographs. arXiv preprint arXiv:1811.00491, 2018.

Shengbang Tong, Ellis Brown, Penghao Wu, Sanghyun Woo, Manoj Middepogu, Sai Charitha Akula, Jihan Yang, Shusheng Yang, Adithya Iyer, Xichen Pan, et al. Cambrian-1: A fully open, vision-centric exploration of multimodal llms. ArXiv preprint, abs/2406.16860, 2024. URL https://arxiv.org/abs/2406.16860.

Dani Valevski, Yaniv Leviathan, Moab Arar, and Shlomi Fruchter. Diffusion models are real-time game engines. arXiv preprint arXiv:2408.14837, 2024.

Fei Wang, Xingyu Fu, James Y Huang, Zekun Li, Qin Liu, Xiaogeng Liu, Mingyu Derek Ma, Nan Xu, Wenxuan Zhou, Kai Zhang, et al. Muirbench: A comprehensive benchmark for robust multi-image understanding. ArXiv preprint, abs/2406.09411, 2024a. URL https://arxiv.org/abs/2406.09411.

Guanzhi Wang, Yuqi Xie, Yunfan Jiang, Ajay Mandlekar, Chaowei Xiao, Yuke Zhu, Linxi Fan, and Anima Anandkumar. Voyager: An open-ended embodied agent with large language models. Transactions on Machine Learning Research, 2023a.

Jing Wang, Weiqing Min, Sujuan Hou, Shengnan Ma, Yuanjie Zheng, Haishuai Wang, and Shuqiang Jiang. Logo-2k+: A large-scale logo dataset for scalable logo classification. In Proceedings of the AAAI Conference on Artificial Intelligence, 2020.

Ke Wang, Junting Pan, Weikang Shi, Zimu Lu, Mingjie Zhan, and Hongsheng Li. Measuring multimodal mathematical reasoning with math-vision dataset, 2024b.

Shengkang Wang, Hongzhan Lin, Ziyang Luo, Zhen Ye, Guang Chen, and Jing Ma. Mfc-bench: Benchmarking multimodal fact-checking with large vision-language models. arXiv preprint arXiv:2406.11288, 2024c.

Xiaoxuan Wang, Ziniu Hu, Pan Lu, Yanqiao Zhu, Jieyu Zhang, Satyen Subramaniam, Arjun R Loomba, Shichang Zhang, Yizhou Sun, and Wei Wang. Scibench: Evaluating college-level scientific problem-solving abilities of large language models. arXiv preprint arXiv:2307.10635, 2023b.

Xin Wang, Jiawei Wu, Junkun Chen, Lei Li, Yuan-Fang Wang, and William Yang Wang. Vatex: A large-scale, high-quality multilingual dataset for video-and-language research. In Proceedings of the IEEE/CVF international conference on computer vision, pp. 4581–4591, 2019.

Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyan Jiang, et al. Mmlu-pro: A more robust and challenging multi-task language understanding benchmark. ArXiv preprint, abs/2406.01574, 2024d.

Zhengqing Wang, Jiacheng Chen, and Yasutaka Furukawa. Puzzlefusion++: Auto-agglomerative 3d fracture assembly by denoise and verify. arXiv preprint arXiv:2406.00259, 2024e.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. Advances in neural information processing systems, 35:24824–24837, 2022.

T. Weyand, A. Araujo, B. Cao, and J. Sim. Google Landmarks Dataset v2 - A Large-Scale Benchmark for Instance-Level Recognition and Retrieval. In Proc. CVPR, 2020.

Bo Wu, Shoubin Yu, Zhenfang Chen, Joshua B Tenenbaum, and Chuang Gan. Star: A benchmark for situated reasoning in real-world videos. arXiv preprint arXiv:2405.09711, 2024.

Haixu Wu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting. Advances in neural information processing systems, 34:22419–22430, 2021.

Yang Wu, Shilong Wang, Hao Yang, Tian Zheng, Hongbo Zhang, Yanyan Zhao, and Bing Qin. An early evaluation of gpt-4v (ision). arXiv preprint arXiv:2310.16534, 2023.

xAI. Grok-1.5 vision preview, 2024. URL https://x.ai/blog/grok-1.5v.

Haotian Xia, Zhengbang Yang, Yun Zhao, Yuqing Wang, Jingxi Li, Rhys Tracy, Zhuangdi Zhu, Yuan-fang Wang, Hanjie Chen, and Weining Shen. Language and multimodal models in sports: A survey of datasets and applications. arXiv preprint arXiv:2406.12252, 2024.

Junbin Xiao, Xindi Shang, Angela Yao, and Tat-Seng Chua. Next-qa: Next phase of question-answering to explaining temporal actions. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 9777–9786, 2021.

Yijia Xiao, Edward Sun, Tianyu Liu, and Wei Wang. Logicvista: Multimodal llm logical reasoning benchmark in visual contexts, 2024. URL https://arxiv.org/abs/2407.04973.

Binzhu Xie, Sicheng Zhang, Zitang Zhou, Bo Li, Yuanhan Zhang, Jack Hessel, Jingkang Yang, and Ziwei Liu. Funqa: Towards surprising video comprehension. arXiv preprint arXiv:2306.14899, 2023.

Jian Xie, Kai Zhang, Jiangjie Chen, Tinghui Zhu, Renze Lou, Yuandong Tian, Yanghua Xiao, and Yu Su. Travelplanner: A benchmark for real-world planning with language agents. In Forty-first International Conference on Machine Learning, 2024.

Ning Xie, Farley Lai, Derek Doran, and Asim Kadav. Visual entailment: A novel task for fine-grained image understanding. arXiv preprint arXiv:1901.06706, 2019.

Shuo Yang, Ping Luo, Chen-Change Loy, and Xiaoou Tang. Wider face: A face detection benchmark. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 5525–5533, 2016.

Yuan Yao, Tianyu Yu, Ao Zhang, Chongyi Wang, Junbo Cui, Hongji Zhu, Tianchi Cai, Haoyu Li, Weilin Zhao, Zhihui He, et al. Minicpm-v: A gpt-4v level mllm on your phone. ArXiv preprint, abs/2408.01800, 2024. URL https://arxiv.org/abs/2408.01800.

Kexin Yi, Chuang Gan, Yunzhu Li, Pushmeet Kohli, Jiajun Wu, Antonio Torralba, and Joshua B Tenenbaum. Clevrer: Collision events for video representation and reasoning. arXiv preprint arXiv:1910.01442, 2019.

Shukang Yin, Chaoyou Fu, Sirui Zhao, Ke Li, Xing Sun, Tong Xu, and Enhong Chen. A survey on multimodal large language models. ArXiv preprint, abs/2306.13549, 2023. URL https://arxiv.org/abs/2306.13549.

Kaining Ying, Fanqing Meng, Jin Wang, Zhiqian Li, Han Lin, Yue Yang, Hao Zhang, Wenbo Zhang, Yuqi Lin, Shuo Liu, et al. Mmt-bench: A comprehensive multimodal benchmark for evaluating large vision-language models towards multitask agi. arXiv preprint arXiv:2404.16006, 2024.

Hang Yu, Yufei Xu, Jing Zhang, Wei Zhao, Ziyu Guan, and Dacheng Tao. Ap-10k: A benchmark for animal pose estimation in the wild. arXiv preprint arXiv:2108.12617, 2021.

Tianyu Yu, Haoye Zhang, Yuan Yao, Yunkai Dang, Da Chen, Xiaoman Lu, Ganqu Cui, Taiwen He, Zhiyuan Liu, Tat-Seng Chua, et al. Rlaif-v: Aligning mllms through open-source ai feedback for super gpt-4v trustworthiness. arXiv preprint arXiv:2405.17220, 2024a.

Weihao Yu, Zhengyuan Yang, Linjie Li, Jianfeng Wang, Kevin Lin, Zicheng Liu, Xinchao Wang, and Lijuan Wang. MM-vet: Evaluating large multimodal models for integrated capabilities. In Ruslan Salakhutdinov, Zico Kolter, Katherine Heller, Adrian Weller, Nuria Oliver, Jonathan Scarlett, and Felix Berkenkamp (eds.), Proceedings of the 41st International Conference on Machine Learning, volume 235 of Proceedings of Machine Learning Research, pp. 57730–57754. PMLR, 2024b. URL https://proceedings.mlr.press/v235/yu24o.html.

Zhou Yu, Dejing Xu, Jun Yu, Ting Yu, Zhou Zhao, Yueting Zhuang, and Dacheng Tao. Activitynet-qa: A dataset for understanding complex web videos via question answering. In Proceedings of the AAAI Conference on Artificial Intelligence, 2019.

Ye Yuan, Xiao Liu, Wondimu Dikubab, Hui Liu, Zhilong Ji, Zhongqin Wu, and Xiang Bai. Syntax-aware network for handwritten mathematical expression recognition. arXiv preprint arXiv:2203.01601, 2022.

Xiang Yue, Yuansheng Ni, Kai Zhang, Tianyu Zheng, Ruoqi Liu, Ge Zhang, Samuel Stevens, Dongfu Jiang, Weiming Ren, Yuxuan Sun, et al. Mmmu: A massive multi-discipline multimodal understanding and reasoning benchmark for expert agi. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 9556–9567, 2024a.

Xiang Yue, Tianyu Zheng, Yuansheng Ni, Yubo Wang, Kai Zhang, Shengbang Tong, Yuxuan Sun, Ming Yin, Botao Yu, Ge Zhang, et al. Mmmu-pro: A more robust multi-discipline multimodal understanding benchmark. arXiv preprint arXiv:2409.02813, 2024b.

Xiaoxue Zang, Lijuan Liu, Maria Wang, Yang Song, Hao Zhang, and Jindong Chen. Photochat: A human-human dialogue dataset with photo sharing behavior for joint image-text modeling. arXiv preprint arXiv:2108.01453, 2021.

Hanlei Zhang, Hua Xu, Xin Wang, Qianrui Zhou, Shaojie Zhao, and Jiayan Teng. Mintrec: A new dataset for multimodal intent recognition. In Proceedings of the 30th ACM International Conference on Multimedia, pp. 1688–1697, 2022.

Yiming Zhang, ZeMing Gong, and Angel X Chang. Multi3drefer: Grounding text description to multiple 3d objects. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 15225–15236, 2023.

Chujie Zheng, Hao Zhou, Fandong Meng, Jie Zhou, and Minlie Huang. Large language models are not robust multiple choice selectors. In The Twelfth International Conference on Learning Representations, 2024.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging llm-as-a-judge with mt-bench and chatbot arena, 2023. URL https://arxiv.org/abs/2306.05685.

Bolei Zhou, Agata Lapedriza, Aditya Khosla, Aude Oliva, and Antonio Torralba. Places: A 10 million image database for scene recognition. IEEE transactions on pattern analysis and machine intelligence, 40(6):1452–1464, 2017.

Haoyi Zhou, Shanghang Zhang, Jieqi Peng, Shuai Zhang, Jianxin Li, Hui Xiong, and Wancai Zhang. Informer: Beyond efficient transformer for long sequence time-series forecasting. In Proceedings of the AAAI conference on artificial intelligence, 2021.

Wang Zhu, Ishika Singh, Robin Jia, and Jesse Thomason. Language models can infer action semantics for classical planners from environment feedback. arXiv preprint arXiv:2406.02791, 2024.

Table of Contents in Appendix

A Single-image Setting: Results and Analyses **23**

B Details of Annotation Protocols **25**
B.1 The unified annotation format 25
B.2 General task collection and creation guidelines 25
B.3 Tools for coordinating annotation and quality control 27

C Taxonomy Tree and Multi-dimensional Keywords **28**
C.1 Details of the Taxonomy Structure 28
C.2 Statistics of each keyword dimension 32

D Evaluation Details **34**
D.1 Prompt template 34
D.2 Model query details 34
D.3 LLM-assisted metrics 35
D.4 Rule-based metrics 36
D.5 Answer extraction from model response 37

E Complete Multi-dimensional Breakdown Results **39**
E.1 Breakdown results on the skill dimension 39
E.2 Breakdown results on the input format dimension 40
E.3 Breakdown results on the output format dimension 41
E.4 Breakdown results on the application dimension 42
E.5 Breakdown results on the visual input number dimension 43

F Detailed Inspection of Model Behaviours on MEGA-BENCH **44**

G Detailed Task Information **66**

A SINGLE-IMAGE SETTING: RESULTS AND ANALYSES

Table 2 in the main paper focuses on models with multi-image support. However, some open-source models are only trained with single images. To provide a feasible evaluation setting for these models, we create a single-image (SI) setting using the single-image tasks in MEGA-BENCH, containing 273 and 42 tasks from the Core and Open-ended sets, respectively.

Evaluation setup. The Chain-of-Thought (CoT) prompting is used for Core SI tasks. To make the entire query contain only one image as needed by some single-image models, we drop the image input of the 1-shot demonstration example ("✗ demo im" column in the table). In this case, the 1-shot example only demonstrates the output format, which is necessary for inferring the correct answer. For those models already evaluated in Table 2, we calculate the task-level average scores on single-image tasks to obtain the "✓ demo im" results. Compared to Table 2, 3 single-image models are evaluated and added: Molmo-72B-0924 (Deitke et al., 2024), Molmo-7B-D-0924 (Deitke et al., 2024), and POINTS-Qwen2.5-7B (Liu et al., 2024b).

Evaluation results. Table 3 presents the evaluation results of the SI setting. The Core and Open-ended scores of the standard setting (with CoT prompting) are also in the table for reference. Some observations from the table are listed below:

• Single-image tasks are easier than multi-image tasks in general, and all models get higher scores in the SI setting than in the standard setting.

• GPT-4o has the best overall SI score, slightly higher than Claude 3.5 Sonnet (1022). Interestingly, GPT-4o mini overtakes Gemini-1.5-Flash-002 under the SI setting, suggesting that Gemini-1.5-Flash has pretty stable performance across different numbers of image inputs.

• NVLM-72B (Dai et al., 2024) has much better scores in the SI setting than in the standard setting, suggesting its training data might only contain single or a few images.

• Comparing the "✓ demo im" and "✗ demo im" results of open-source models, the image input in the 1-shot demonstration example is not well utilized by the models to better understand the task logic. Including the image input in the demonstration example makes the results much worse for models like Llama-3.2-11B.

More detailed breakdown results are available on our project page and the leaderboard (hosted with Hugging Face Spaces)

Table 3: The single-image (SI) setting results of MEGA-BENCH. The Core set evaluation uses Chain-of-Thought (CoT) prompting. The "demo img" means the image input of the 1-shot demonstration example. The "✓ demo im" directly takes the single-image subset average from the full results in Table 2. The "✗ demo im" means the 1-shot demonstration example only demonstrates the output format, and the entire query has a single image. We report "✓ demo im" alone for the proprietary models because they have good multi-image support. For open-source models, we do additional evaluations with the "✗ demo im" setting and use it to compute the overall score.

Model	Core	Core SI		Open	Open SI		Overall SI
		✓ demo im	✗ demo im		✓ demo im	✗ demo im	
GPT-4o (0513) (OpenAI, 2024a)	52.65	**55.30**	-	64.78	66.00	-	**56.73**
Claude-3.5-Sonnet (1022) (Anthropic, 2024b)	52.59	54.63	-	65.63	**67.64**	-	56.36
Claude-3.5-Sonnet (0620) (Anthropic, 2024a)	50.41	52.03	-	63.74	64.80	-	53.73
Gemini-1.5-Pro-002 (Google, 2024b)	48.22	49.14	-	58.58	58.15	-	50.34
GPT-4o mini (OpenAI, 2024b)	40.77	**44.31**	-	58.65	**59.56**	-	**46.32**
Gemini-1.5-Flash-002 (Google, 2024b)	41.89	43.48	-	56.91	57.87	-	45.40
Qwen2-VL-72B (Alibaba, 2024)	45.42	**47.31**	**47.31**	56.40	**58.50**	55.10	**48.34**
InternVL2-Llama3-76B (Chen et al., 2024d)	35.63	39.32	39.99	51.93	55.33	**55.47**	42.05
Molmo-72B-0924 (Deitke et al., 2024)	-	-	36.48	-	-	44.66	37.58
NVLM-72B (Dai et al., 2024)	21.59	31.19	32.99	34.78	48.67	44.69	34.55
LLaVA-OneVision-72B (Li et al., 2024a)	29.74	31.77	31.26	45.99	46.12	44.26	32.99
Qwen2-VL-7B (Alibaba, 2024)	32.93	**35.04**	**35.39**	43.96	45.87	45.17	**36.69**
Pixtral-12B (Mistral, 2024)	31.36	34.87	34.37	45.66	44.03	44.17	35.68
Aria-MoE-25B (Li et al., 2024d)	28.90	31.67	31.79	51.03	**50.92**	**51.37**	34.40
InternVL2-8B (Chen et al., 2024d)	24.09	27.19	27.65	39.79	40.94	39.39	29.21
Phi-3.5-Vision-4B (Abdin et al., 2024)	23.00	25.72	25.61	39.48	44.61	42.72	27.89
POINTS-Qwen2.5-7B (Liu et al., 2024b)	-	-	25.51	-	-	30.32	26.15
MiniCPM-V2.6-8B (Yao et al., 2024)	22.96	23.82	23.23	41.73	42.54	43.61	25.95
LLaVA-OneVision-7B (Li et al., 2024a)	21.36	22.70	23.68	33.98	36.44	38.71	25.69
Qwen2-VL-2B (Alibaba, 2024)	20.88	24.16	22.78	31.54	30.59	35.09	24.43
Molmo-7B-D (Deitke et al., 2024)	-	-	20.98	-	-	35.70	22.95
Llama-3.2-11B (Meta, 2024)	16.00	17.34	20.79	31.73	34.29	38.61	23.17
Aquila-VL-2B-llava-qwen (Gu et al., 2024)	16.00	16.98	20.77	24.57	24.58	31.47	22.20
InternVL2-2B (Chen et al., 2024d)	13.14	13.83	12.07	23.86	24.28	28.52	14.26
Idefics3-8B-Llama3 (Laurençon et al., 2024)	8.96	9.13	8.94	32.11	33.25	32.31	12.06

B DETAILS OF ANNOTATION PROTOCOLS

This section presents additional details of our task annotation pipeline and protocols, providing complete details for §3.1 of the main paper.

B.1 THE UNIFIED ANNOTATION FORMAT

Figure 8 presents the annotation format designed and used in our annotation process. All annotated tasks share this unified structure, including task instruction, *optional* global media to provide context to all the questions (typically used in retrieval-related tasks). Additionally, each specific example contains distinct media path(s), a concrete question, and an answer with a single or multiple answer fields. Multi-field answers are organized as JSON structures.

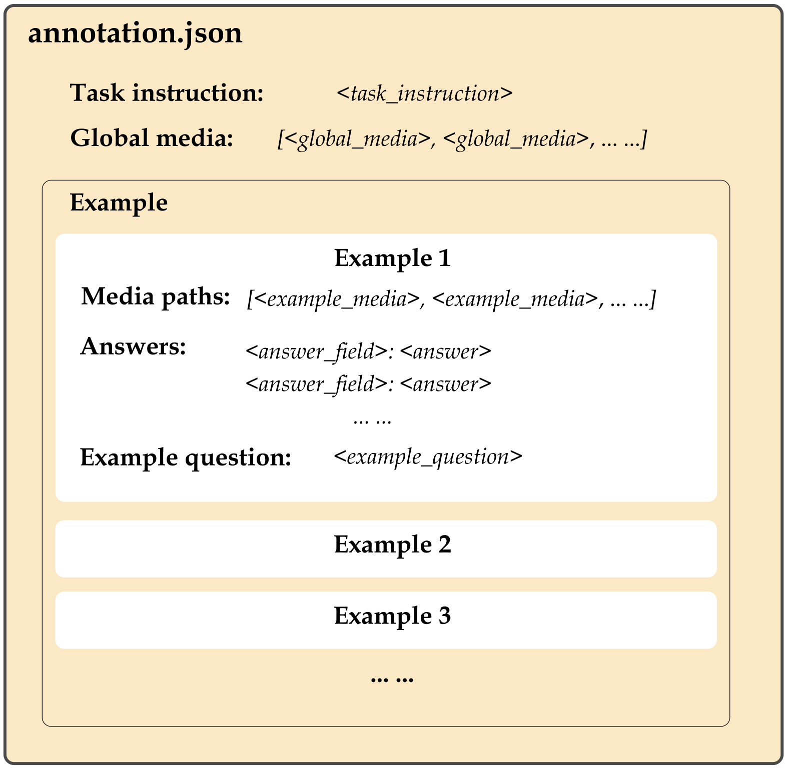

annotation.json
Task instruction: <task_instruction>
Global media: [<global_media>, <global_media>, ...]
Example
Example 1
Media paths: [<example_media>, <example_media>, ...]
Answers: <answer_field>: <answer>
<answer_field>: <answer>
... ...
Example question: <example_question>
Example 2
Example 3
... ...

Figure 8: The structure of our task annotation format, which helps coordinate all task annotators and standardize the annotation format.

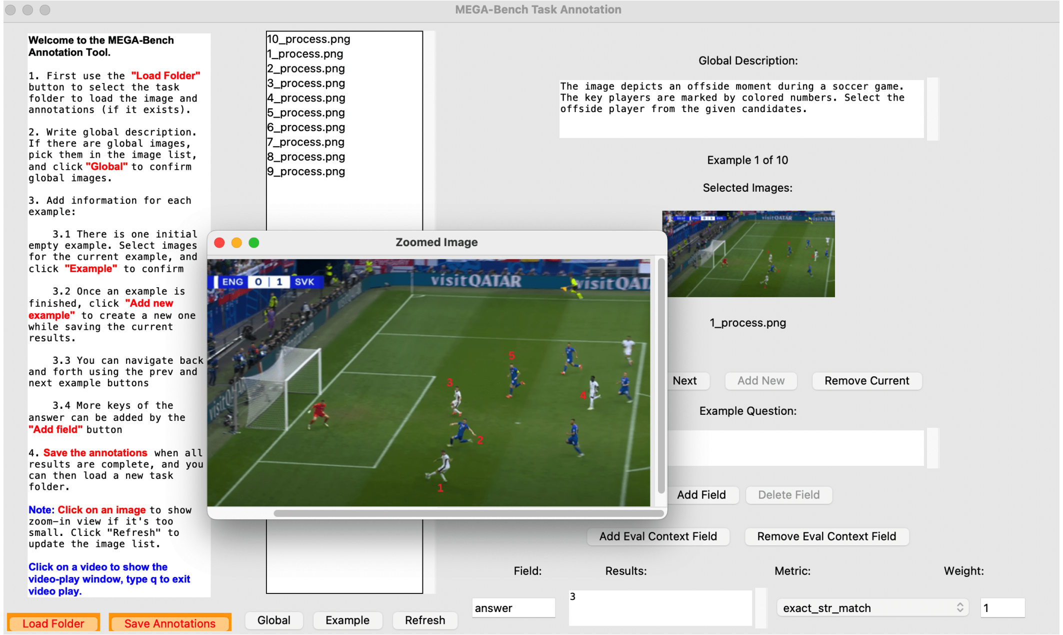
Our evaluation pipeline follows this format to convert the task information into concrete queries and feed them to the evaluated model. Based on this format, we establish an interactive annotation tool to ensure the tasks submitted by all annotators have the correct and unified format. Figure 9 demonstrates the GUI of the annotation tool.

B.2 GENERAL TASK COLLECTION AND CREATION GUIDELINES

This subsection provides more detailed annotation guidelines for our annotators, complementing the descriptions in §3.1.

Data source of each task. There is no restriction on the data source as long as the annotator follows the copyright and license requirements of the original data. Below are three typical task types and their data sources:

(1). The task is designed entirely by the annotator, and the annotator looks for the image or video resources from the Internet or even using code/simulator;



Welcome to the MEGA-Bench Annotation Tool.

1. First use the **"Load Folder"** button to select the task folder to load the image and annotations (if it exists).

2. Write global description. If there are global images, pick them in the image list, and click **"Global"** to confirm global images.

3. Add information for each example:

    3.1 There is one initial empty example. Select images for the current example, and click **"Example"** to confirm

    3.2 Once an example is finished, click **"Add new example"** to create a new one while saving the current results.

    3.3 You can navigate back and forth using the prev and next example buttons

    3.4 More keys of the answer can be added by the **"Add field"** button

4. **Save the annotations** when all results are complete, and you can then load a new task folder.

Note: Click on an image to show zoom-in view if it's too small. Click "Refresh" to update the image list.

Click on a video to show the video-play window, type q to exit video play.

10_process.png
1_process.png
2_process.png
3_process.png
4_process.png
5_process.png
6_process.png
7_process.png
8_process.png
9_process.png

Global Description:

The image depicts an offside moment during a soccer game. The key players are marked by colored numbers. Select the offside player from the given candidates.

1_process.png

Field:	Results:	Metric:	Weight:
answer	3	exact_str_match	1

Figure 9: A screenshot of our GUI annotation tool.

(2). The task is inspired by existing benchmarks or datasets. The annotator collects the raw image/video data from existing datasets but does not use the original annotation. The annotator redesigns/repurposes the data by writing concrete task descriptions and creating new questions and answers, or using scripts to re-process the data for the designed task.

(3). The task is directly converted from existing benchmarks or datasets. The annotator randomly samples a subset from the existing benchmark, directly using its image/video and the annotation without redesign.

In our annotation process, the first two task types are encouraged. The task reviewers strictly control the number of the third type and reject the task if an annotator submits many tasks of the third type. Table 18 shows the detailed data source of all tasks in MEGA-BENCH.

Output format and answer uniqueness. We aim to cover diverse output formats in MEGA-BENCH. Therefore, we always require the task annotators to consider adapting the original dataset's answer format, especially avoiding unnecessary multiple-choice questions (many MCQs are unnatural and mainly for evaluation convenience). Notably, the annotator must provide sufficient context in the task description and per-example question so that the range of the correct answer is manageable and the task can be evaluated with a clearly defined metric.

Metric specification. When creating a task, the annotator must specify the corresponding evaluation metric. Since the metric implementation is in parallel to the task construction process, as described in §3.2, our GUI annotation tool (Figure 9) allows annotators to choose from existing metrics for each answer field of the task and assigns different weights to each field. When the desired metric is unavailable, the annotator chooses an "unsupported" metric type and writes down detailed metric specifications in the pull request. Our core contributors periodically check the needs of new metrics and implement them.

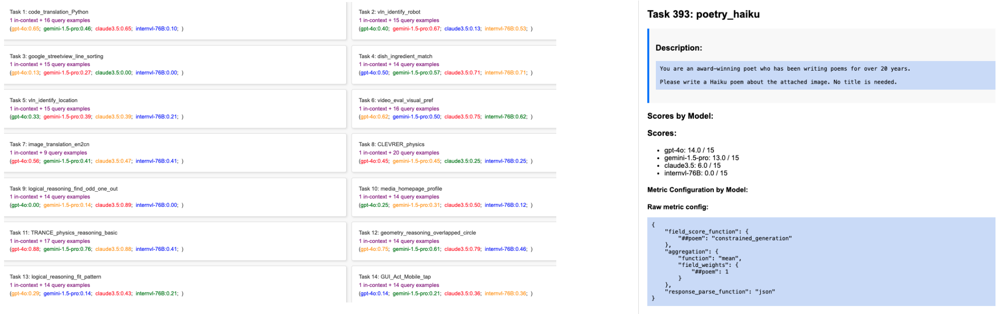
Documentation. When submitting the pull request, the annotator must write README documentation for each task. If the desired metric has not been implemented, the documentation should contain the specification described in the last point. Furthermore, the doc should record the data source (e.g., the Web, an existing dataset, etc.) and brief descriptions of the task. These descriptions are instrumental in helping the core contributors assign various keywords to the task and creating Table 18 to show the details of all tasks.

B.3 TOOLS FOR COORDINATING ANNOTATION AND QUALITY CONTROL

As described in §3.1, we have two additional tools for coordinating the annotation process and maintaining the data. We present the details in this subsection.

The GitHub repository for task organization. We created a private GitHub repository for constructing MEGA-BENCH. The repository's main branch is protected, and all task submissions must go through pull requests (PRs). The core contributors serve as the task reviewers and discuss with task annotators in the pull request forum to ensure the task conforms to our data collection guidelines (§B.2). The code of our evaluation pipeline, including the model query and score computation, is maintained in the same repository. The core contributors submit pull requests to support different VLMs and add new evaluation metrics, and these PRs are cross-reviewed by other core contributors.

We also actively use the repository's Issues forum to report bugs in annotation or metric implementation so the corresponding contributors can get notified and work on the fix. At the end of the annotation process, our repository has 685 pull requests and 40 issues. 277 out of the 685 PRs are for task submission, indicating that many annotators submit task groups with more than one task in each PR. Other PRs are mainly for the evaluation pipeline and bug fixing.



Task 1: code_translation_Python
1 in-context + 16 query examples
(gpt-4o:0.65; gemini-1.5-pro:0.46; claude3.5:0.65; internvl-76B:0.10;)

Task 2: vln_identify_robot
1 in-context + 15 query examples
(gpt-4o:0.40; gemini-1.5-pro:0.67; claude3.5:0.13; internvl-76B:0.53;)

Task 3: google_streetview_line_sorting
1 in-context + 15 query examples
(gpt-4o:0.13; gemini-1.5-pro:0.27; claude3.5:0.00; internvl-76B:0.00;)

Task 4: dish_ingredient_match
1 in-context + 14 query examples
(gpt-4o:0.50; gemini-1.5-pro:0.57; claude3.5:0.71; internvl-76B:0.71;)

Task 5: vln_identify_location
1 in-context + 15 query examples
(gpt-4o:0.33; gemini-1.5-pro:0.39; claude3.5:0.39; internvl-76B:0.21;)

Task 6: video_eval_visual_pref
1 in-context + 16 query examples
(gpt-4o:0.62; gemini-1.5-pro:0.50; claude3.5:0.75; internvl-76B:0.62;)

Task 7: image_translation_en2cn
1 in-context + 9 query examples
(gpt-4o:0.56; gemini-1.5-pro:0.41; claude3.5:0.47; internvl-76B:0.41;)

Task 8: CLEVRER_physics
1 in-context + 20 query examples
(gpt-4o:0.45; gemini-1.5-pro:0.45; claude3.5:0.25; internvl-76B:0.25;)

Task 9: logical_reasoning_find_odd_one_out
1 in-context + 14 query examples
(gpt-4o:0.00; gemini-1.5-pro:0.14; claude3.5:0.89; internvl-76B:0.00;)

Task 10: media_homepage_profile
1 in-context + 14 query examples
(gpt-4o:0.25; gemini-1.5-pro:0.31; claude3.5:0.50; internvl-76B:0.12;)

Task 11: TRANCE_physics_reasoning_basic
1 in-context + 17 query examples
(gpt-4o:0.88; gemini-1.5-pro:0.76; claude3.5:0.88; internvl-76B:0.41;)

Task 12: geometry_reasoning_overlapped_circle
1 in-context + 14 query examples
(gpt-4o:0.75; gemini-1.5-pro:0.61; claude3.5:0.79; internvl-76B:0.46;)

Task 13: logical_reasoning_fit_pattern
1 in-context + 14 query examples
(gpt-4o:0.29; gemini-1.5-pro:0.14; claude3.5:0.43; internvl-76B:0.21;)

Task 14: GUI_Act_Mobile_tap
1 in-context + 14 query examples
(gpt-4o:0.14; gemini-1.5-pro:0.21; claude3.5:0.36; internvl-76B:0.36;)

(a). List of existing tasks

Task 393: poetry_haiku

Description:

```
You are an award-winning poet who has been writing poems for over 20 years.

Please write a Haiku poem about the attached image. No title is needed.
```

Scores by Model:

Scores:

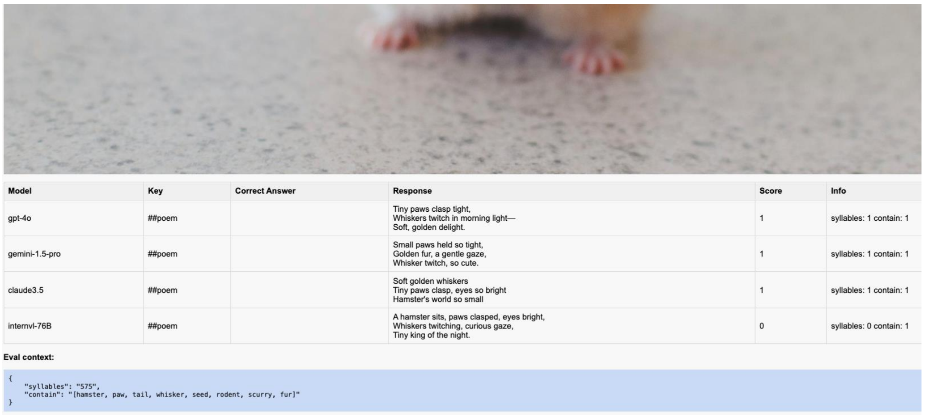
- gpt-4o: 14.0 / 15
- gemini-1.5-pro: 13.0 / 15
- claude3.5: 6.0 / 15
- internvl-76B: 0.0 / 15

Metric Configuration by Model:

Raw metric config:

```
{
    "field_score_function": {
        "##poem": "constrained_generation"
    },
    "aggregation": {
        "function": "mean",
        "field_weights": {
            "##poem": 1
        }
    },
    "response_parse_function": "json"
}
```

(b). Task overview



Model	Key	Correct Answer	Response	Score	Info
gpt-4o	##poem		Tiny paws clasp tight, Whiskers twitch in morning light— Soft, golden delight.	1	syllables: 1 contain: 1
gemini-1.5-pro	##poem		Small paws held so tight, Golden fur, a gentle gaze, Whisker twitch, so cute.	1	syllables: 1 contain: 1
claude3.5	##poem		Soft golden whiskers Tiny paws clasp, eyes so bright Hamster's world so small	1	syllables: 1 contain: 1
internvl-76B	##poem		A hamster sits, paws clasped, eyes bright, Whiskers twitching, curious gaze, Tiny king of the night.	0	syllables: 0 contain: 1

Eval context:

```
{
    "syllables": "575",
    "contain": "[hamster, paw, tail, whisker, seed, rodent, scurry, fur]"
}
```

(c). Per-example model response and evaluation results

Figure 10: Illustrations of our task visualization page.

Task visualization web page. We developed a simple visualization web page and periodically synchronized the evaluation results of existing tasks on the page. The page provides several benefits: 1) it allows the core contributors to keep track of the overall annotation process, 2) it helps the annotators understand the capability of state-of-the-art VLMs, so that they can adjust the task difficulty accordingly, and 3) it facilitates the checking of the potential annotation glitches or metric bugs, significantly improving the overall quality of MEGA-BENCH. Figure 10 shows screenshots of the visualization page taken during the benchmark construction process. Note that the task names in the figure might not align with the final names in the paper. In our project page, we will provide a similar visualization page for users to interactively inspect the behaviors of different VLMs.

C TAXONOMY TREE AND MULTI-DIMENSIONAL KEYWORDS

This section presents the full details of our application-based taxonomy tree and the multi-dimensional keywords.

C.1 DETAILS OF THE TAXONOMY STRUCTURE

Table 4 shows the detailed structure of our application-driven task taxonomy. The first level defines the broad scope of use cases. At the second level, tasks are categorized into more specific domains. These first two levels guide the annotation process of our benchmark and are gradually updated/refined in the annotation process. The third level lists the concrete names of tasks or task groups. If the third-level node is a task group, the number of concrete tasks under this group is shown in the parenthesis.

Table 4: Details of taxonomy of MEGA-BENCH.

Level-2 Tasks	Leaf Tasks (at Level-3 or deeper)	# Tasks
Coding		
Code Debugging	Stackoverflow Debug Qa, Code Error Line Identification	2
Code Generation	Document Conversion (8 tasks), Programming Problems (4 tasks), Visualization With Code	13
Code Translation	Code Translation Easy, Code Translation Python, Code Translation Hard, Code Translation Advanced	4
Code Understanding	Symbolic Graphics Programming (2 tasks), Webpage Code Understanding, Code Add Tag, Code Match (5 tasks), Code Output (3 tasks)	12
Information Extraction		
App Function Understanding	App Layout Understanding Leetcode, App Layout Understanding Youtube, App Layout Understanding Amazon, App Layout Understanding Word, App Layout Understanding Notes, App Layout Understanding Ppt, App Layout Understanding Alipay, App Layout Understanding Instagram, App Layout Understanding Zoom, App Layout Understanding Excel, App Layout Understanding Iphone Settings, App Layout Understanding Tiktok, App Layout Understanding Twitter	13
Compound Search and Calculate	Cheapest Flight Identification, Weather Info Retrieval, Stock Info Retrieval, Game Platform Support Identification, Top Rated Hotel Identification, Movie Info Retrieval, Top Video Creator Identification, Highest Discount Game Price Identification, Newspaper Page Parse And Count, Remaining Playback Time Calculation	10
Detailed Manual Understanding	Multi Lingual Manual Explanation Scooter Spanish, Multi Lingual Manual Explanation Scooter Arabic, Multi Lingual Manual Explanation Scooter French, Multi Lingual Manual Explanation Scooter Chinese, Multi Lingual Manual Explanation Scooter Russian	5
Multimodal QA	Multilingual News Qa, Product Ocr Qa, Large Image (3 tasks), Gui Chat (2 tasks), Realworld Qa En2cn, Star Object Interaction Video, Video Qa (7 tasks)	16

Table 4 – continued from previous page

Level-2 Tasks	Leaf Tasks (at Level-3 or deeper)	# Tasks
Search by Attribute wo Calculate	Coco Ood Global Image Retrieval By Query Property, Places365 Similar Scene Retrieval, Booking Web Recommendation, Game Info Retrieval, Media Homepage Profile, Movie Retrieval By Actor, Music Info Retrieval, Tv Show Retrieval By Character	8
Structured Parsing	Multilingual Movie Info Parsing, Movie Info Parsing, Stock Info Parsing, Music Info Parsing, Multilingual Game Info Parsing, Ocr Article Authors, Youtube Video Info Parsing, Tv Show Info Parsing, Ocr Resume School Plain, Image Translation En2cn, Booking Web Rating, Weather Info Parsing, Game Info Parsing, Weather Map Climate Type Temperature Parsing, Hotel Booking Confirmation Parsing, Entertainment Web Game Style	16
Summarization	Video Summary, Video Short Title, Video2notes, Video Content Reasoning	4
	Knowledge	
Arts	Poetry Generation (7 tasks), Ascii Art 30	8
Fact Checking	Background Change, Out Of Context, Text Entity Replace, Text Style, Face Attribute Edit, Face Swap, Interpret Force Perspective Illusion, Clip Stable Diffusion Generate, Unusual Images, Forensic Detection Of Different Images, Veracity, Distinguish Ai Generated Image	12
Human and Culture	Cultural Vqa, Human Relationship Reasoning, Sign Language, Ishihara Test, Safety And Norm (13 tasks), Video Content Follow Up, Emotion And Intent Understanding (9 tasks), Theory Of Minds (2 tasks), Hashtag Recommendation	30
World Knowledge	Dish Ingredient Match, Music (6 tasks), Insect Order Classification, Signage Navigation, Song Title Identification From Lyrics, Logo And Sign (3 tasks), Chinese Idiom Recognition, Ruozhiba (6 tasks), Font Recognition, Traffic Accident Analysis, Multiple State Identification (4 tasks), Worldle, Location Vqa, Daily (2 tasks), Ancient Map Understanding, Rocks Samples Compare, Painting (2 tasks), Memorization (4 tasks), Soccer Offside, Deciphering Oracle Bone, Actor Character And Famous People (3 tasks), Landmark And Buliding (3 tasks), Defeasible Reasoning	47
	Mathematics	
Algebra	Algebra	1
Calculus	Scibench Calculus Wo Solution	1
Functions	Math Parity, Math Breakpoint, Math Convexity Value Estimation	3
General	Math Exams V, Theoremqa, Math	3

Table 4 – continued from previous page

Level-2 Tasks	Leaf Tasks (at Level-3 or deeper)	# Tasks
Geometry	Geometry Reasoning Count Line Intersections, Geometry Length, Geometry Reasoning Nested Squares, Geometry Transformation, Geometry Reasoning Overlapped Circle, Geometry Area, Geometry Reasoning Grid, Polygon Interior Angles, Geometry Solid, Geometry Analytic, Geometry Descriptive	11
Graph Theory	Graph Shortest Path Kamada Kawai, Graph Shortest Path Planar, Graph Connectivity, Graph Theory, Graph Isomorphism, Graph Hamiltonian Cycle, Graph Hamiltonian Path, Graph Chordless Cycle, Topological Sort, Graph Maxflow	10
Number Theory	Counterfactual Arithmetic	1
Numeric Reasoning	Clevr Arithmetic, Iconqa Count And Reasoning, Number Comparison	3
	Metrics	
Generated Image Eval	Autorater Artifact, Autorater Control, Autorater Artifact Reason, Autorater Aesthetics, Autorater Unmask, Autorater Subject, Autorater 3d Model Texturing, Autorater Semantics, Autorater Motion Guided Editing, Autorater Mask	10
Generated Video Eval	Video Eval Visual Pref, Generated Video Artifacts, Video Eval Factual Pref, Video Eval Dynamic Pref	4
Paper Review	Paper Review Writing, Paper Review Rating, Paper Review Acceptance	3
Quality Assessment	Vizwiz Quality Accessment For Blind	1
Reward Models	Reward Models T2i Reward, Reward Models I2t Reward	2
	Perception	
3D understanding	Adapted Cvbench Depth, Relative Depth Of Different Points, Visual Prediction Rater Depth Estimation, Visual Prediction Rater Novel View Synthesis, Pokemon 3d Recognition, Av View Identification, Multiview Reasoning Camera Moving, 3d Indoor Scene Text Bbox Prediction, Google Streetview Circle Reasoning, Google Streetview Direction Understanding, Video Motion Matching Real 3d, Video Motion Matching 3d Real, Visual Prediction Rater 3d Assembled Quality Understanding, Visual Prediction Rater Surface Normal Estimation, Visual Prediction Rater Plane Segmentation, 3d Indoor Scene Text Bbox Selection, Google Streetview Circle Sorting	17
Counting	Ad Count Detection, Adapted Cvbench Count, Av Vehicle Multiview Counting, Counting Multi Image, Av Human Multiview Counting, Shape Composition Shapes, Counting Single Image, Clevrer Video Moving Object Count, Shape Composition Colours	9
Diagram and Document Understanding	Diagram (23 tasks), Document (9 tasks), Table Qa (6 tasks)	38

Table 4 – continued from previous page

Level-2 Tasks	Leaf Tasks (at Level-3 or deeper)	# Tasks
Image Segmentation	Visual Prediction Rater Openable Part Segmentation, Visual Prediction Rater Panoptic Segmentation, Visual Prediction Rater Semantic Segmentation	3
Multimodal Captioning	Video Detail Description, Guess Image Generation Prompt, Docci Image Description Long, Tweets Captioning, Image Captioning With Additional Requirements	5
Multimodal Constrained Captioning	Contain Contain Images, Contain Repeat Length, Multi Contain Repeat Position Only Length, Contain Length, Contain Position Images, Contain Position Length, Xor Images, Multi Contain Repeat, Contain Contain Length, Multi Contain Position Only	10
Object and Scene Understanding	Autonomous Driving Scene Analysis, Super Clevr Scene Understanding, Functionality Matching In Different Objects, Visual Dialog Image Guessing, Nlvr2 Two Image Compare Qa, Egocentric Analysis Single Image, Clevrer Object Existence Video, Snli Ve Visual Entailment, Ocr Open Ended Qa, Semantic Matching Of Two Images	10
Physical Understanding	Physical Reasoning (8 tasks), Lighting And Shading (2 tasks)	10
Spatial Understanding	Adapted Cvbench Relation, Visual Correspondance In Two Images, 2d Image Jigsaw Puzzle Easy, Geometry Plot Position Relationship, Adapted Cvbench Distance, Video Grounding Spatial, Egocentric Spatial Reasoning	7
Temporal Understanding	Video To Camera Trajectory Retrieval, Sceneqa Scene Transition Video, Video Segments Reordering, Video Action Recognition, Action Sequence Understanding, Google Streetview Line Sorting, Next Action Prediction, Perception Test Video Action Count, Google Streetview Line Reasoning, Video Camera Motion Description, Video Grounding Temporal, Web Action Prediction, Cam Traj To Video Selection, Sta Action Localization Video	14
Visual Recognition	Face Identity Matching, Rocks Samples Identify, Animal Pose Estimation, License Plate Recognition, Image Style Recognition, Long String Letter Recognition, Coco Object Detection By Query Property, Widerface Face Count And Event Classification, Handwritten Math Expression Extraction, Geometry Reasoning Circled Letter, Av Multicamera Tracking Predict Bbox, Ascii Art Understanding, Face Keypoint Detection, Extract Webpage Headline, Waldo, Geographic Remote Sensing Land Cover, Signboard Identification, Long String Number Recognition, Waybill Number Sequence Extraction, Single Person Pose Estimation, Coco Person Detection, Places365 Scene Type Classification	22
Planning		

Table 4 – continued from previous page

Level-2 Tasks	Leaf Tasks (at Level-3 or deeper)	# Tasks
Agents and Planning	Wikihow Complex Task Completion, Navigation (6 tasks), Gui Operation (18 tasks), Calendar Schedule Suggestion, Symbolic Planning (13 tasks)	39
Puzzles and Games	Logical Reasoning Find Odd One Out, Logical Reasoning Fit Pattern, Perception Test Object Shuffle Video, Board Games (12 tasks), Bongard Problem, Number Puzzle Kakuro 5x5, Mensa Iq Test, Arc Agi, Mnist Pattern, Number Puzzle Sudoku, Move Pos To Pos Hanoi 4 Pole, Pictionary (5 tasks), Annoying Word Search, Logical Reasoning 2d Views Of 3d Shapes, Maze 2d 8x8, Crossword Mini 5x5, Rebus, Icon Arithmetic Puzzle, Iq Test Open Ended, Ball Cup Swap 3, Logical Reasoning 2d Folding	36
Reordering	Perception Test Video Character Order, Comic Page Ordering, Recipe Image Ordering	3
Science		
Chemistry	Chemistry Exams V, Science Molecule Chemistry	2
Life Sciences	Biology Exams V, Medical (15 tasks)	16
Physics	Circuit Diagram Understanding, Mmmu Physics Chemistry Selected, Science Basic Physics, Physics Exams V	4
STEM	Mmmu Pro Exam Screenshot, Scibench W Solution Open Ended, Arxiv Vqa, Tqa Textbook Qa, Question Solution Solving, Quizlet Question Solving, Scibench Fundamental Wo Solution	7

C.2 STATISTICS OF EACH KEYWORD DIMENSION

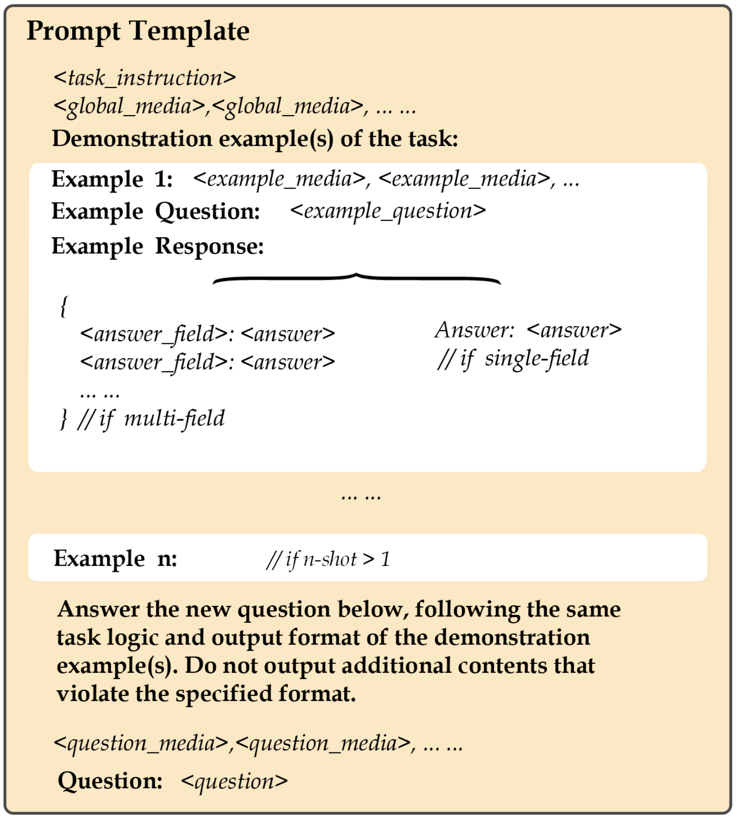
Figure 2 of the main paper presented the overall keyword distribution. As a complement, Table 5 provides more detailed statistics. Each of the five dimensions contains multiple keywords, and for each keyword, we explicitly show the number of related tasks and the total number of samples.

Table 5: Number of tasks and samples across the five dimensions, with detailed breakdown into each keyword.

Dimension	**Keywords (number of tasks, num of samples)**
Skills	Object Recognition (303, 4755), OCR (137, 2239), Language Parsing & Gen. (154, 2509), Scene & Event Understanding (154, 2467), Math & Logical Reasoning (109, 1910), Commonsense & Social Reasoning (51, 855), Ethical & Safety Reasoning (15, 245), Domain-Specific Knowledge/Skills (77, 1387), Spatial & Temporal Reasoning (152, 2437), Planning & Decision Making (37, 577)
Input Format	User Interface (93, 1517), Text-rich Image & Doc (82, 1294), Diagrams & Visualizations (101, 1718), Videos (43, 698), Artistic & Creative (32, 542), Photographs (143, 2248), 3D Related (11, 169)
Output Format	Contextual Formatted (98, 1514), Structured (110, 1714), Exact (83, 1279), Numerical (49, 862), Open-ended (80, 1454), Multiple Choice (85, 1363)
Input Number	6-8 images (21, 314), 9-image+ (41, 623), 1-image (315, 5228), Video (43, 698), 4-5 images (34, 520), 2-3 images (51, 802)
Application	Information_Extraction (72, 1124), Planning (78, 1239), Coding (31, 474), Perception (145, 2313), Metrics (20, 309), Science (29, 574), Knowledge (97, 1605), Mathematics (33, 547)

D EVALUATION DETAILS

This section details our evaluation settings, including the prompt template design, model query details, and evaluation metrics.



Prompt Template

<task_instruction>
<global_media>,<global_media>, ...
Demonstration example(s) of the task:

Example 1: *<example_media>, <example_media>, ...*
Example Question: *<example_question>*
Example Response:

{
<answer_field>: <answer>
<answer_field>: <answer>
... ...
} // if multi-field

Answer: <answer>
// if single-field

... ...

Example n: *// if n-shot > 1*

Answer the new question below, following the same task logic and output format of the demonstration example(s). Do not output additional contents that violate the specified format.

<question_media>,<question_media>, ...
Question: *<question>*

Figure 11: The prompt template structure without Chain-of-Thought (CoT).

D.1 PROMPT TEMPLATE

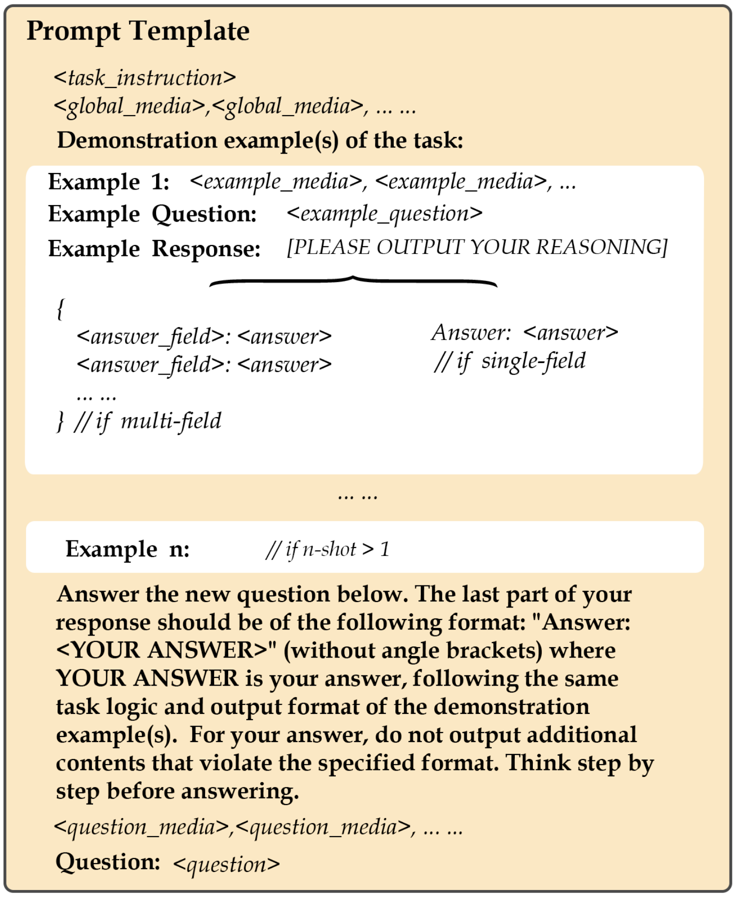
We provide the concrete prompt template in Figure 11 and Figure 12. All the information organized by the prompt template is serialized by our evaluation pipeline before sending queries to the evaluated model.

The non-CoT prompt instructs the VLM to strictly follow the one-shot example, directly producing the answer without additional text. In contrast, the CoT prompt instructs the VLM to output step-by-step reasoning before providing the final answer, and the model must strictly separate the reasoning process from the final answer.

Note that our prompt sets different formats for single-field and multi-field outputs. Single-field answers must be explicitly indicated by the "Answer: ..." format so that our output parser can robustly locate and extract the model's answer. Multi-field answers are in JSON format, and our JSON parser can robustly extract the JSON-style answer from the entire response without the "Answer: ..." format.

D.2 MODEL QUERY DETAILS

Since the evaluated VLMs have different context windows, we must tailor the number of query images or video frames for each model. We implement an image/video pre-processing pipeline that follows the settings listed in Table 6 to sub-sample the input images and videos. We allocate different budgets for in-context examples and the query. Since the in-context examples (we use a



Prompt Template

<task_instruction>
<global_media>,<global_media>, ...

Demonstration example(s) of the task:

Example 1: *<example_media>, <example_media>, ...*
Example Question: *<example_question>*
Example Response: *[PLEASE OUTPUT YOUR REASONING]*

{
<answer_field>: <answer>
<answer_field>: <answer>
... ...
} // if multi-field

Answer: <answer>
// if single-field

... ...

Example n: *// if n-shot > 1*

Answer the new question below. The last part of your response should be of the following format: "Answer: <YOUR ANSWER>" (without angle brackets) where YOUR ANSWER is your answer, following the same task logic and output format of the demonstration example(s). For your answer, do not output additional contents that violate the specified format. Think step by step before answering.

<question_media>,<question_media>, ...

Question: *<question>*

Figure 12: The prompt template structure for the Chain-of-Thought (CoT) setting

one-shot example) mainly help models understand the task logic and the output format, we reserve most of the image budget for the query. Images or video frames surpassing the budget are discarded. To make sure the open-source models can run smoothly, we implement a fallback strategy, which reduces the image budget to decrease the number of input tokens if the model's maximum context length is exceeded.

For images or video frames with a longer side larger than 1000 pixels, we resize the longer side to 1000 without changing the aspect ratio before sending them to the evaluated model. Each

D.3 LLM-ASSISTED METRICS

The LLM-assisted metric instructs a multimodal LLM to evaluate VLM's response by providing a detailed evaluation prompt. When submitting a task with open-ended answers that cannot be evaluated by rule-based metrics, the annotator is asked to write down a detailed evaluation prompt for the LLM judge following the prompt format in Figure 13.

Concretely, the task annotator decides if the LLM judge should consider the question's visual input when evaluating the model's response. If yes, then the query media (images or videos) will be passed to the LLM as well (we use GPT-4o-0806 as a multimodal judge model). For most tasks, the LLM judge can do a proper evaluation by comparing the model's response with the reference answer, and the visual media is not needed. The task annotator also writes a thorough evaluation criteria, explaining to the judge model the meaning of each score range, which is important to get reliable evaluation results.

Table 6: The maximum number of images and the budget for the in-context example per model.

Model	**Max # of images**	**In-context example budget**
GPT-4o (0513) (OpenAI, 2024a)	64	8
Claude-3.5-Sonnet (1022) (Anthropic, 2024a)	64	8
Claude-3.5-Sonnet (0620) (Anthropic, 2024a)	64	8
Gemini-1.5-Pro-002 (Google, 2024b)	128	16
Gemini-1.5-Flash-002 (Google, 2024b)	128	16
GPT-4o Mini (OpenAI, 2024b)	64	8
Qwen2-VL-72B (Alibaba, 2024)	24	2
InternVL2-Llama3-76B (Chen et al., 2024d)	24	4
NVLM-72B Dai et al. (2024)	32	4
Molmo-72B-0924 (Deitke et al., 2024)	1	0
LLaVA-OneVision-72B (Li et al., 2024a)	28	4
Qwen2-VL-7B (Alibaba, 2024)	18	2
Pixtral-12B (Mistral, 2024)	48	6
Aria-MoE-25B (Li et al., 2024d)	32	4
POINTS-Qwen2.5-7B (Liu et al., 2024b)	1	0
InternVL2-8B (Chen et al., 2024d)	18	2
Phi-3.5-Vision (Abdin et al., 2024)	16	2
MiniCPM-V2.6 (Yao et al., 2024)	64	8
Molmo-7B-D (Deitke et al., 2024)	1	0
LLaVA-OneVision-7B (Li et al., 2024a)	20	4
Llama-3.2-11B (Meta, 2024)	32	4
Idefics3-8B-Llama3 (Laurençon et al., 2024)	20	2
Qwen2-VL-2B (Alibaba, 2024)	16	2
InternVL2-2B (Chen et al., 2024d)	18	2
Aquila-VL-2B-llava-qwen (Gu et al., 2024)	8	1

LLM-Assisted Metrics Prompt Template

<media>,<media>, ... // if judge with image
<evaluation_criteria> // defined by task annotator
Reference: *<reference_answer>*
Model Response: *<model_response>*
(Optional): *<per_example_label>*
// some tasks require per-example criteria
Please output your score in the following format:
Score: <single_number>,
Score explanation: <detailed_explanations>

Figure 13: The prompt template structure for LLM-Assisted Metrics

At the end of the prompt, a pre-defined scoring format instruction is attached, ensuring the judge model outputs a score between 1 and 10 and an explanation for the score.

D.4 RULE-BASED METRICS

We have over 40 highly customized rule-based metrics to evaluate the Core set of MEGA-BENCH. Basic metrics like "extract string match" and "simple string match" (which ignores punctuation and special characters) are first added to the supported metric set. New metrics are implemented when our task annotators submit new tasks requiring uncovered metrics. In the end, we get 45 customized tasks, as shown in Table 7. The usage distribution is long-tail because many metric implementations are triggered by a single novel task.

Table 7: All metrics used in MEGA-BENCH.

Metric Name	Usage Count (# tasks)
Exact String Match	198
GPT-4o as Judge	64
Simple String Match	61
Multi Reference Phrase Evaluation	25
Constrained Generation	18
Set Equality	15
Sequence Equality	15
General Single Numerical Match	14
Exact String Match Case Insensitive	14
Sequence Accuracy Case Insensitive	13
Symbolic Planning Test	13
String Set Equality Comma	9
Normalized RMSE	8
Program Judge	8
Set Precision	5
Dictionary Equality	4
String Set Equality Line Break	4
Sequence Coordinates Similarity	3
LaTeX Expression Equality	3
Jaccard Index Case Insensitive	3
Jaccard Index	3
Normalized Bounding Box IOU Tuple	2
Number Relative Difference Ratio	2
XML Bounding Box IOU	2
Dictionary Exact String Match Aggregate Recall	2
Boxed Single Numerical Match	2
Positive Integer Match	2
Chess Move List Jaccard Index	2
Code Result Exact String Match	1
Normalized Bounding Box IOU Single	1
Normalized Bounding Box IOU Sequence	1
Normalized Similarity Damerau-Levenshtein	1
Near String Match	1
XML Normalized Point Distance	1
Dictionary Precision	1
Text with LaTeX Expression Equality	1
Angle Sequence Float RMSE	1
XML Normalized Point in Bounding Box	1
Longest Common List Prefix Ratio	1
Sequence Equality Case Insensitive	1
Set Equality Case Insensitive	1
GLEU (Chinese)	1
ASCII Art GPT-4O Judge	1
Dictionary Jaccard Aggregate Jaccard	1
Dictionary Normalized Bounding Box IOU Tuple Aggregate Jaccard	1

D.5 ANSWER EXTRACTION FROM MODEL RESPONSE

For Core tasks, our rule-based evaluation metrics compare the model's answer with a ground-truth answer or some ground-truth constraints. Therefore, an answer extraction step is necessary to separate the final answer from the reasoning process and other irrelevant texts. We implement robust extraction logic for different types of outputs based on the format specified in the prompt template:

Single-field answer. We first reduce the answer by the "Answer: ..." pattern. If this pattern does not exist, we take the entire response. Since many VLMs do not strictly follow the format instructions, we have specific and extra processing for different output formats to improve robustness. Some typical examples are: 1) For multiple-choice outputs, we locate the exact letter or index choice using sophisticated regular expressions, which excludes any potential parenthesis or accompanying texts; 2) For code outputs, we extract the code from the potential code blocks; 3) For structured outputs, we parse the structural data into the proper Python data structures (list, set, dictionary, etc.), with tolerance on minor syntax errors (e.g., we automatically fix wrong quotes).

Multi-field answer. Since the prompt requires the model to output the final answer in JSON format, we implement a robust JSON parser to locate the JSON structure in the raw response and convert the JSON structure into the corresponding Python data structure.

If our comprehensive answer extraction fails to obtain any meaningful final answer from the model response, we consider the model as “fail to follow instructions”.

E COMPLETE MULTI-DIMENSIONAL BREAKDOWN RESULTS

This section provides the full breakdown results over the five dimensions of MEGA-BENCH, complementing section 4 of the main paper.

E.1 BREAKDOWN RESULTS ON THE SKILL DIMENSION

Table 8: Average scores for each model on the *skill* dimension. The best-performing model in each category is **in-bold**, and the second best is underlined.

Model	**CASR**	**DKAS**	**EASR**	**LUAG**	**MALR**	**ORAC**	**PADM**	**SAEU**	**SATR**	**TR**
Claude-3.5-Sonnet (1022) (Anthropic, 2024b)	59.1	54.9	65.7	60.8	**48.9**	**56.9**	**29.1**	55.1	**43.2**	**62.2**
GPT-4o (0513) (OpenAI, 2024a)	**63.5**	**55.1**	68.0	**61.6**	44.2	56.3	22.9	**58.2**	39.4	62.2
Claude-3.5-Sonnet (0620) (Anthropic, 2024a)	57.6	52.8	69.7	57.5	47.7	54.1	23.8	54.5	40.8	60.8
Gemini-1.5-Pro-002 (Google, 2024b)	57.5	51.4	**69.8**	55.3	42.6	52.0	23.9	54.7	38.5	50.2
Gemini-1.5-Flash-002 (Google, 2024b)	55.9	44.8	63.8	49.9	34.4	46.3	19.0	51.0	34.5	43.4
GPT-4o mini (OpenAI, 2024b)	55.7	41.9	69.0	51.7	34.1	44.9	19.4	46.7	29.4	49.0
Qwen2-VL-72B (Alibaba, 2024)	56.8	46.3	60.5	53.9	37.8	49.8	22.0	50.9	35.1	54.4
InternVL2-Llama3-76B (Chen et al., 2024d)	52.6	33.3	57.8	43.7	29.8	38.2	17.0	42.7	29.5	41.3
LLaVA-OneVision-72B (Li et al., 2024a)	47.8	31.7	60.1	36.7	29.5	36.2	13.9	42.1	29.6	28.3
NVLM-72B (Dai et al., 2024)	40.9	25.8	45.6	29.4	26.4	24.0	6.7	22.8	15.7	32.2
Qwen2-VL-7B (Alibaba, 2024)	49.4	33.3	52.2	40.3	28.2	37.1	14.7	41.1	27.6	40.2
Pixtral 12B (Mistral, 2024)	41.9	32.8	56.9	38.3	28.3	34.6	10.6	37.8	26.8	37.8
Aria-MoE-25B (Li et al., 2024d)	49.4	32.8	58.1	40.0	27.6	32.6	11.9	37.8	24.8	35.7
InternVL2-8B (Chen et al., 2024d)	39.7	27.1	47.0	32.0	24.1	28.2	8.3	32.6	23.2	28.1
Phi-3.5-Vision (Abdin et al., 2024)	36.8	24.1	46.7	28.7	21.7	25.5	8.9	30.5	21.5	24.8
MiniCPM-V2.6 (Yao et al., 2024)	40.7	23.7	48.8	30.0	18.3	26.0	8.7	31.8	19.7	25.0
LLaVA-OneVision-7B (Li et al., 2024a)	36.8	24.5	45.0	25.6	19.0	25.2	6.7	30.0	21.8	19.1
Qwen2-VL-2B (Alibaba, 2024)	31.3	20.8	41.4	25.7	17.6	22.2	6.2	26.5	17.3	23.7
Llama-3.2-11B (Meta, 2024)	32.3	17.7	42.6	19.6	13.3	19.1	6.6	22.4	15.4	14.3
Aquila-VL-2B-llava-qwen (Gu et al., 2024)	26.6	18.6	35.2	17.9	16.8	18.4	4.5	22.0	16.2	12.4
InternVL2-2B (Chen et al., 2024d)	24.0	14.8	34.2	16.9	13.9	14.5	1.7	18.5	13.0	12.1
Idefics3-8B-Llama3 (Laurençon et al., 2024)	19.2	17.9	28.6	17.3	13.3	14.5	4.2	14.7	10.2	11.6

The abbreviations used in the table above are explained in the following table:

Table 9: Abbreviation list of the keywords in the *skill* dimension.

Abbreviation	**Skill**
CASR	Commonsense and Social Reasoning
DKAS	Domain-Specific Knowledge and Skills
EASR	Ethical and Safety Reasoning
LUAG	Language Understanding and Generation
MALR	Mathematical and Logical Reasoning
ORAC	Object Recognition and Classification
PADM	Planning and Decision Making
SAEU	Scene and Event Understanding
SATR	Spatial and Temporal Reasoning
TR	Text Recognition (OCR)

E.2 BREAKDOWN RESULTS ON THE INPUT FORMAT DIMENSION

Table 10: Average scores for each model on the *input format* dimension. The best-performing model in each category is **in-bold**, and the second best is underlined.

Model	3MAAI	AACC	DADV	P	TIAD	UIS	V
Claude-3.5-Sonnet (1022) (Anthropic, 2024b)	44.2	55.6	**55.6**	54.3	48.9	60.5	49.5
GPT-4o (0513) (OpenAI, 2024a)	**47.8**	56.4	50.0	**56.1**	**49.1**	**60.8**	**53.2**
Claude-3.5-Sonnet (0620) (Anthropic, 2024a)	44.3	**57.0**	52.6	51.0	48.0	56.9	50.9
Gemini-1.5-Pro-002 (Google, 2024b)	42.9	55.8	48.7	55.0	42.9	46.3	50.3
Gemini-1.5-Flash-002 (Google, 2024b)	38.5	50.5	40.1	51.7	36.0	38.7	49.0
GPT-4o mini (OpenAI, 2024b)	29.4	47.6	38.9	46.5	36.2	47.2	45.5
Qwen2-VL-72B (Alibaba, 2024)	36.2	50.8	42.1	49.8	42.9	54.0	49.9
InternVL2-Llama3-76B (Chen et al., 2024d)	28.7	45.0	34.7	42.9	31.4	36.3	39.6
LLaVA-OneVision-72B (Li et al., 2024a)	23.9	44.0	34.6	42.5	21.3	23.4	44.5
NVLM-72B (Dai et al., 2024)	5.7	34.7	30.3	32.6	21.7	23.9	0.0
Qwen2-VL-7B (Alibaba, 2024)	26.2	34.8	32.2	40.7	29.0	38.2	41.1
Pixtral 12B (Mistral, 2024)	24.0	37.5	32.2	37.1	28.8	30.7	41.0
Aria-MoE-25B (Li et al., 2024d)	19.6	36.1	32.4	37.3	27.8	28.3	42.9
InternVL2-8B (Chen et al., 2024d)	10.9	29.4	28.0	33.9	20.1	22.8	34.8
Phi-3.5-Vision (Abdin et al., 2024)	15.4	27.9	26.1	34.1	17.5	18.7	24.7
MiniCPM-V2.6 (Yao et al., 2024)	7.6	31.0	21.6	31.8	18.6	21.2	35.3
LLaVA-OneVision-7B (Li et al., 2024a)	13.0	32.0	24.2	32.6	13.3	14.7	31.0
Qwen2-VL-2B (Alibaba, 2024)	13.4	24.9	19.6	28.8	16.3	19.1	25.2
Llama-3.2-11B (Meta, 2024)	6.4	25.2	16.9	24.9	11.5	11.9	21.2
Aquila-VL-2B-llava-qwen (Gu et al., 2024)	10.1	19.7	19.4	24.6	11.4	7.5	21.4
InternVL2-2B (Chen et al., 2024d)	11.9	14.9	16.3	20.1	10.5	5.7	19.0
Idefics3-8B-Llama3 (Laurençon et al., 2024)	4.0	18.4	16.2	14.9	11.4	10.1	16.2

The abbreviations used in the table above are explained in the following table:

Table 11: Abbreviation list of the keywords in the *input formats* dimension.

Abbreviation	Input Format
3MAAI	3D Models and Aerial Imagery
AACC	Artistic and Creative Content
DADV	Diagrams and Data Visualizations
P	Photographs
TIAD	Text-Based Images and Documents
UIS	User Interface Screenshots
V	Videos

E.3 BREAKDOWN RESULTS ON THE OUTPUT FORMAT DIMENSION

Table 12: Average scores for each model on the *output format* dimension. The best-performing model in each category is **in-bold**, and the second best is underlined.

Model	**C**	**E**	**M**	**N**	**O**	**S**
Claude-3.5-Sonnet (1022) (Anthropic, 2024b)	51.9	53.9	**57.8**	**48.2**	62.4	**50.7**
GPT-4o (0513) (OpenAI, 2024a)	**53.9**	**59.9**	54.5	44.6	**62.7**	48.0
Claude-3.5-Sonnet (0620) (Anthropic, 2024a)	50.7	52.8	54.6	44.9	58.4	49.7
Gemini-1.5-Pro-002 (Google, 2024b)	44.9	51.5	55.4	46.9	55.8	44.4
Gemini-1.5-Flash-002 (Google, 2024b)	38.7	44.8	47.8	37.0	54.5	39.9
GPT-4o mini (OpenAI, 2024b)	41.2	44.2	39.9	36.3	57.1	39.1
Qwen2-VL-72B (Alibaba, 2024)	44.7	51.0	52.0	40.3	51.6	45.0
InternVL2-Llama3-76B (Chen et al., 2024d)	36.3	39.4	38.8	29.2	45.8	34.8
LLaVA-OneVision-72B (Li et al., 2024a)	28.7	37.1	39.9	30.7	42.9	25.9
NVLM-72B (Dai et al., 2024)	22.9	27.9	18.5	23.3	32.2	27.9
Qwen2-VL-7B (Alibaba, 2024)	34.3	35.2	39.9	32.7	39.1	34.3
Pixtral 12B (Mistral, 2024)	30.8	36.4	30.1	32.1	41.7	31.9
Aria-MoE-25B (Li et al., 2024d)	30.9	29.3	32.8	30.9	45.2	30.4
InternVL2-8B (Chen et al., 2024d)	25.1	27.4	30.3	22.4	35.4	25.2
Phi-3.5-Vision (Abdin et al., 2024)	21.8	25.7	26.0	21.4	36.5	21.4
MiniCPM-V2.6 (Yao et al., 2024)	23.5	25.5	29.3	20.8	36.5	17.8
LLaVA-OneVision-7B (Li et al., 2024a)	20.3	25.4	28.0	22.0	31.3	18.3
Qwen2-VL-2B (Alibaba, 2024)	16.2	20.0	25.7	22.0	30.2	21.0
Llama-3.2-11B (Meta, 2024)	12.4	15.8	19.3	15.0	30.0	16.4
Aquila-VL-2B-llava-qwen (Gu et al., 2024)	11.9	18.5	22.1	19.9	23.3	12.3
InternVL2-2B (Chen et al., 2024d)	11.3	15.5	21.3	16.0	21.4	5.7
Idefics3-8B-Llama3 (Laurençon et al., 2024)	14.0	7.1	11.6	9.8	29.9	10.6

The abbreviations used in the table above are explained in the following table:

Table 13: Abbreviation list of keywords in the *output formats* dimension.

Abbreviation	**Output Format**
C	Contextual Formatted Text
E	Exact Text
M	Multiple Choice
N	Numerical Data
O	Open-ended Output
S	Structured Output

E.4 BREAKDOWN RESULTS ON THE APPLICATION DIMENSION

Table 14: Average scores for each model on the *application* dimension. The best-performing model in each category is **in-bold**, and the second best is underlined.

Model	C	I	K	M	M2	P	P2	S
Claude-3.5-Sonnet (1022) (Anthropic, 2024b)	51.7	65.9	56.6	**47.6**	**61.2**	**55.6**	**39.9**	**55.1**
GPT-4o (0513) (OpenAI, 2024a)	50.3	**70.6**	**61.4**	44.0	61.0	55.1	33.2	52.8
Claude-3.5-Sonnet (0620) (Anthropic, 2024a)	**51.9**	66.6	55.1	47.5	58.1	53.2	33.8	51.3
Gemini-1.5-Pro-002 (Google, 2024b)	43.5	54.2	57.2	41.2	58.2	52.5	33.4	51.2
Gemini-1.5-Flash-002 (Google, 2024b)	40.4	46.6	51.2	33.7	60.1	48.0	25.2	45.7
GPT-4o mini (OpenAI, 2024b)	34.6	56.7	54.0	32.9	51.8	43.6	24.2	35.5
Qwen2-VL-72B (Alibaba, 2024)	43.7	58.1	51.7	31.2	49.7	53.6	31.2	44.9
InternVL2-Llama3-76B (Chen et al., 2024d)	29.5	43.1	46.3	28.7	47.4	42.2	21.3	30.0
LLaVA-OneVision-72B (Li et al., 2024a)	23.2	30.8	43.6	31.6	48.1	38.4	18.2	31.7
NVLM-72B (Dai et al., 2024)	23.9	22.8	37.2	24.5	18.9	30.2	8.0	24.9
Qwen2-VL-7B (Alibaba, 2024)	32.7	42.7	42.8	25.6	42.5	40.0	20.0	29.9
Pixtral 12B (Mistral, 2024)	25.7	43.0	38.1	24.2	50.2	38.9	13.6	31.3
Aria-MoE-25B (Li et al., 2024d)	28.5	38.3	41.0	26.2	39.7	37.8	14.3	29.7
InternVL2-8B (Chen et al., 2024d)	24.7	29.1	33.9	22.1	40.0	32.1	12.2	24.6
Phi-3.5-Vision (Abdin et al., 2024)	21.9	22.4	33.3	17.6	39.5	31.6	8.9	21.9
MiniCPM-V2.6 (Yao et al., 2024)	15.3	26.7	33.2	16.5	37.8	29.2	11.7	25.7
LLaVA-OneVision-7B (Li et al., 2024a)	15.2	19.3	32.7	22.1	36.0	28.5	9.8	23.7
Qwen2-VL-2B (Alibaba, 2024)	17.0	25.2	26.6	16.4	31.0	27.6	7.0	21.1
Llama-3.2-11B (Meta, 2024)	5.8	17.3	28.1	13.9	25.4	19.9	8.1	16.3
Aquila-VL-2B-llava-qwen (Gu et al., 2024)	13.3	9.5	24.1	20.7	29.3	20.7	5.9	21.1
InternVL2-2B (Chen et al., 2024d)	11.3	8.7	21.2	11.0	33.3	17.0	4.1	16.9
Idefics3-8B-Llama3 (Laurençon et al., 2024)	9.1	14.7	17.6	13.2	14.6	14.6	5.4	22.7

The abbreviations used in the table above are explained in the following table:

Table 15: Abbreviation list of keywords in the *applications* dimension .

Abbreviation	Application
C	Coding
I	Information-Extraction
K	Knowledge
M	Mathematics
M2	Metrics
P	Perception
P2	Planning
S	Science

E.5 BREAKDOWN RESULTS ON THE VISUAL INPUT NUMBER DIMENSION

Table 16: Average scores for each model on the *visual input number* dimension. The best-performing model in each category is **in-bold**, and the second best is underlined.

Model	1	2I	4I	6I	9OM	V
Claude-3.5-Sonnet (1022) (Anthropic, 2024b)	56.4	48.8	48.3	46.3	**59.1**	49.5
GPT-4o (0513) (OpenAI, 2024a)	**56.7**	49.1	45.0	**47.5**	53.4	**53.2**
Claude-3.5-Sonnet (0620) (Anthropic, 2024a)	53.7	**49.3**	44.2	46.3	54.1	50.9
Gemini-1.5-Pro-002 (Google, 2024b)	50.3	45.5	**48.9**	39.1	53.7	50.3
Gemini-1.5-Flash-002 (Google, 2024b)	44.3	42.0	42.3	33.7	43.7	49.0
GPT-4o mini (OpenAI, 2024b)	46.3	37.0	24.7	33.6	43.1	45.5
Qwen2-VL-72B (Alibaba, 2024)	49.2	45.2	36.7	31.0	54.7	49.9
InternVL2-Llama3-76B (Chen et al., 2024d)	41.5	31.5	24.4	20.3	34.8	39.6
LLaVA-OneVision-72B (Li et al., 2024a)	34.8	34.2	25.0	20.7	28.1	44.5
NVLM-72B (Dai et al., 2024)	36.8	23.3	3.8	0.0	0.0	0.0
Qwen2-VL-7B (Alibaba, 2024)	37.7	33.0	26.4	19.4	37.5	41.1
Pixtral 12B (Mistral, 2024)	37.1	31.0	25.8	19.7	16.6	41.0
Aria-MoE-25B (Li et al., 2024d)	35.8	27.3	19.8	21.1	27.1	42.9
InternVL2-8B (Chen et al., 2024d)	30.1	25.3	17.7	15.4	19.9	34.8
Phi-3.5-Vision (Abdin et al., 2024)	27.8	28.5	20.2	12.5	14.3	24.7
MiniCPM-V2.6 (Yao et al., 2024)	26.3	22.3	17.9	14.0	23.6	35.3
LLaVA-OneVision-7B (Li et al., 2024a)	25.5	24.1	17.8	14.8	13.8	31.0
Qwen2-VL-2B (Alibaba, 2024)	25.0	21.3	17.4	7.7	10.5	25.2
Llama-3.2-11B (Meta, 2024)	19.6	18.6	13.5	14.6	7.3	21.2
Aquila-VL-2B-llava-qwen (Gu et al., 2024)	18.2	23.3	19.0	11.1	1.2	21.4
InternVL2-2B (Chen et al., 2024d)	15.2	15.8	17.7	3.7	5.8	19.0
Idefics3-8B-Llama3 (Laurençon et al., 2024)	14.8	12.3	12.2	10.1	9.3	16.2

The abbreviations used in the table above are explained in the following table:

Table 17: Abbreviation list of keywords in the *visual input number* dimension.

Abbreviation	Input Number
1	1-image
2I	2-3 images
4I	4-5 images
6I	6-8 images
9OM	9-image or more
V	video

F DETAILED INSPECTION OF MODEL BEHAVIOURS ON MEGA-BENCH

To complement §4.3 of the main paper, this section presents a case study analysis of the error types of different models on different tasks in MEGA-BENCH. We use similar error categories as in MMMU (Yue et al., 2024a) and MMT-Bench (Ying et al., 2024):

- **Perception Error**: VLMs fail to recognize or perceive the content of interest in the query image(s). Perception errors indicate the

- **Lack of Knowledge**: VLMs lack the domain-specific knowledge to answer specialized questions, such as identifying the taxonomic order of an insect.

- **Lack of (Reasoning) Capability**: VLMs lack the necessary capabilities to solve the task, mainly related to various reasoning abilities, such as logical reasoning, counting, spatial or temporal reasoning, symbolic reasoning for code or various programs, and so on. This is a broad type that covers many errors. One typical case for this error type is that the models can accurately follow instructions and perceive the visual inputs but struggle with the required reasoning process, leading to incorrect answers.

- **Refuse to Answer**: VLMs refuse to answer questions that they believe to involve sensitive content.

- **Fail to Follow Instructions**: VLMs fail to correctly understand instructions and provide wrong answers. The tasks in MEGA-BENCH usually have more instructions on the answer format compared to previous benchmarks. A typical error pattern is not comprehending the required format, thus providing answers with incorrect formats or generating irrelevant responses. This error type is much more common in open-source models.

Figure 14 to Figure 33 shows the case study for samples from different tasks. We use distinct colors to highlight the tags in each task sample. We borrow the error case analysis template from MMMU (Yue et al., 2024a) while adding the keywords information of MEGA-BENCH. We mainly focus on the flagship proprietary models. The Claude-3.5 in these figures refers to the Claude-3.5-Sonnet (0620) model.

List of Figures Depicting Model Behaviors

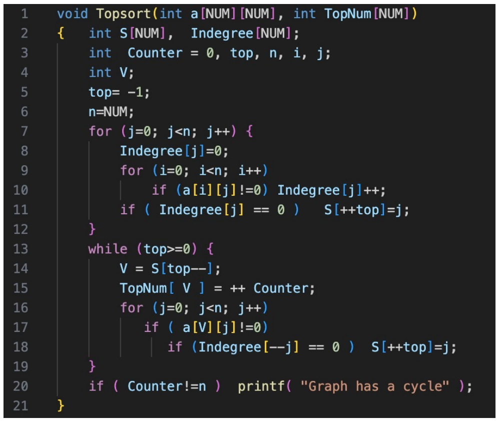
14 Coding - Code Debugging: Error Case 46
15 Coding - Code Understanding: Error Case 1 47
16 Coding - Code Understanding: Error Case 2 48
17 Information Extraction - Multimodel QA: Error Case 49
18 Information Extraction - Detailed Manual Understanding: Error Case 50
19 Information Extraction - Search by Attribute without Calculate: Error Case 51
20 Knowledge - World Knowledge: Error Case 1 52
21 Knowledge - World Knowledge: Error Case 2 53
22 Knowledge - Art: Error Case 54
23 Mathematics - Graph Theory: Error Case 55
24 Metrics - Generated Image Eval: Error Case 1 56
25 Metrics - Generated Image Eval: Error Case 2 57
26 Planning - Puzzles and Games: Error Case 1 58
27 Planning - Puzzles and Games: Error Case 2 59
28 Planning - Reordering: Error Case 60
29 Perception - Multimodal Constrained Captioning: Error Case 61
30 Perception - Visual Recognition: Error Case 1 62
31 Perception - Visual Recognition: Error Case 2 63
32 Perception - Visual Recognition: Error Case 3 64
33 Science - STEM: Error Case 65

Coding: Code Debugging

Task Name: Code Error Line Identification

Given a piece of program code, identify the most obvious error. Output the line number on the left where the error occurs. Attention: Do not invoke any external compilers or related programs.
Question: Where the error occurs?

Keywords: **Domain-Specific Knowledge and Skills, Text-Based Images and Documents, Mathematical and Logical Reasoning, Multiple Choice**



```
1   void Topsort(int a[NUM][NUM], int TopNum[NUM])
2   {   int S[NUM],  Indegree[NUM];
3       int  Counter = 0, top, n, i, j;
4       int V;
5       top= -1;
6       n=NUM;
7       for (j=0; j<n; j++) {
8           Indegree[j]=0;
9           for (i=0; i<n; i++)
10              if (a[i][j]!=0) Indegree[j]++;
11          if ( Indegree[j] == 0 )   S[++top]=j;
12      }
13      while (top>=0) {
14          V = S[top--];
15          TopNum[ V ] = ++ Counter;
16          for (j=0; j<n; j++)
17             if ( a[V][j]!=0)
18                if (Indegree[--j] == 0 )  S[++top]=j;
19      }
20      if ( Counter!=n )  printf( "Graph has a cycle" );
21  }
```

Claude-3.5: 1. The function declaration and variable initializations seem correct. 2. The first nested loop (lines 7-12) appears to b e properly structured. 3. The while loop (lines 13-19) also seems structurally correct. 4. However, within this while loop, there's an issue on line 18: 5. This error is the most obvious and significant in the code, as it will likely cause runtime errors or incorrect results. Therefore, the most obvious error occurs on line 18.
Answer: 18 (score: 1.0)

Error Category: Lack of Capability
GPT-4o: The most obvious error in the code is the use of `printf` instead of `printf` in line 20. The correct function name should be `printf`.
Answer: 20 (score: 0.0)

Correct Answer: 18

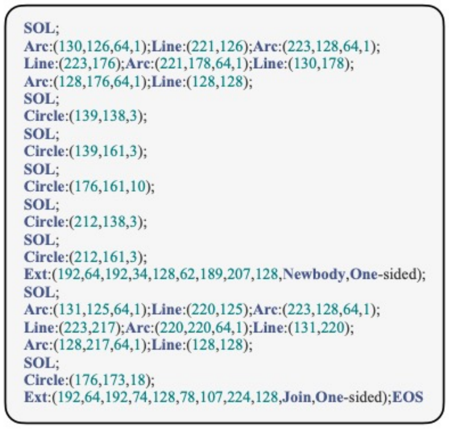
Figure 14: A sample error case of Coding (subfield: Code Debugging). Source:Web
Back to List of Figures

Coding: Code Understanding

Task Name: Symbolic Graphics Programs Computer Aided Design

Given a symbolic graphics program, the task is to answer a related question by understanding the program.
Question: How many visible screws or screw holes are there on the CAD object?

Keywords: **Mathematical and Logical Reasoning, Contextual Formatted Text, Domain-Specific Knowledge and Skills, Text-Based Images and Documents**



```
SOL;
Arc:(130,126,64,1);Line:(221,126);Arc:(223,128,64,1);
Line:(223,176);Arc:(221,178,64,1);Line:(130,178);
Arc:(128,176,64,1);Line:(128,128);
SOL;
Circle:(139,138,3);
SOL;
Circle:(139,161,3);
SOL;
Circle:(176,161,10);
SOL;
Circle:(212,138,3);
SOL;
Circle:(212,161,3);
Ext:(192,64,192,34,128,62,189,207,128,Newbody,One-sided);
SOL;
Arc:(131,125,64,1);Line:(220,125);Arc:(223,128,64,1);
Line:(223,217);Arc:(220,220,64,1);Line:(131,220);
Arc:(128,217,64,1);Line:(128,128);
SOL;
Circle:(176,173,18);
Ext:(192,64,192,74,128,78,107,224,128,Join,One-sided);EOS
```

Claude-3.5: 1. In CAD programs, screws or screw holes are often represented by circles. 2. Looking at the program, we can see several Circle commands: …
Answer: 4 (score: 1.0)

Error Category: Lack of Capability
GPT-4o: To determine the number of visible screws or screw holes in the CAD object, we need to identify the instances of circles in the program, as circles typically represent screws or screw holes in CAD drawings …
Answer: 6 (score: 0.0)

Error Category: Lack of Capability
Gemini-1.5-pro: The code shows six circles that could be screw holes and two "Ext" commands that specify extrusions. Extrusions can be used to create screw holes.
Answer: 8 (score: 0.0)

Correct Answer: 4

Figure 15: A sample error case of Coding (subfield: Code Understanding).
Source:Web

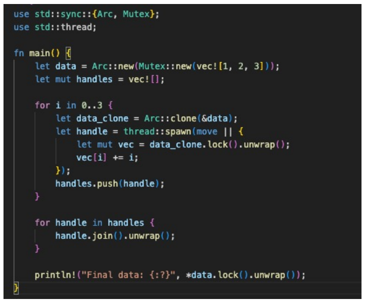
Back to List of Figures

Coding: Code_Understanding

Task Name: Code Output Result

Given several images of program code, output the program's execution result. Attention: Do not invoke any external compilers or related programs. Place the code output in a Markdown result code block.
Question: What's the output of the program?

Keywords: **OCR, Mathematical and Logical Reasoning**
Domain-Specific Knowledge, Text-Based Images and Documents



```rust
use std::sync::{Arc, Mutex};
use std::thread;

fn main() {
    let data = Arc::new(Mutex::new(vec![1, 2, 3]));
    let mut handles = vec![];

    for i in 0..3 {
        let data_clone = Arc::clone(&data);
        let handle = thread::spawn(move || {
            let mut vec = data_clone.lock().unwrap();
            vec[i] += i;
        });
        handles.push(handle);
    }

    for handle in handles {
        handle.join().unwrap();
    }

    println!("Final data: {:?}", *data.lock().unwrap());
}
```

Error Category: Lack of Capability
Claude 3.5 : Let's analyze this Rust code step by step:
1. We start with a vector [1, 2, 3] wrapped in an Arc<Mutex<...>>.
2. We create an empty vector `handles` to store thread handles.
3. We spawn 3 threads (for i in 0..3):
- Each thread gets a clone of the Arc.
- Each thread locks the mutex and increments the first element of the vector.
4. After spawning, we join all threads, ensuring they complete.
5. Finally, we print the contents of the vector.
Let's trace the changes:
- Initial state: [1, 2, 3]
- Thread 1: [2, 2, 3]
- Thread 2: [3, 2, 3]
- Thread 3: [4, 2, 3]
The final state of the vector will be [4, 2, 3]. The println! macro will output this vector.
Answer: Final data: [4, 2, 3] (score: 0.0)

Correct Answer: Final data: [1, 3, 5]

Figure 16: A sample error case of Coding (subfield: Code Understanding).
Source:Web

Back to List of Figures

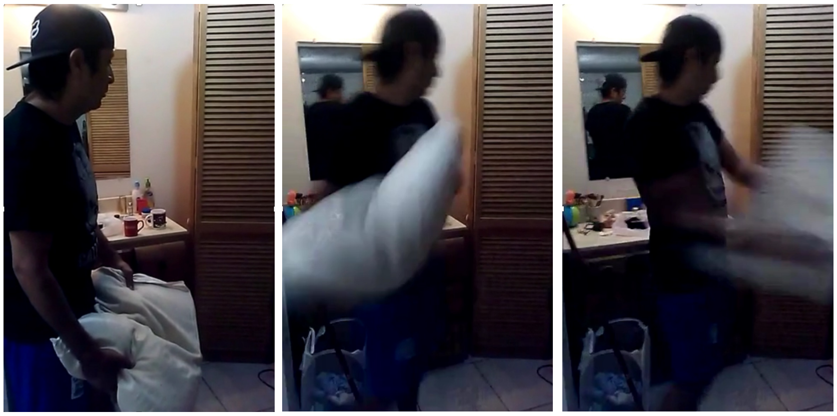
Information Extraction: Multimodel QA

Task Name: Object Interaction Video

The task involves identifying objects a person interacts with in various videos based on the provided questions. You need to output the object name.
Question: Which object was taken by the person?

Keywords: **Contextual Formatted Text, Scene Understanding, Scene and Event Understanding, Videos**

...



...

GPT-4o: Answer: pillow (score: 1.0)

Error Category: Perception Error
Claude-3.5: After carefully analyzing the sequence of images, I can see that the person in the video is interacting with a hat. In the earlier frames, the person is holding what appears to be a white or light-colored object, which is likely laundry or bedding. However, as the sequence progresses, we see the person in front of a mirror, and they appear to be adjusting or handling a hat. In the final frames, there's a motion that suggests the person is tossing or throwing the hat upwards.
Answer: hat (score: 0.0)

Correct Answer: **pillow**

Figure 17: A sample error case of Information Extraction (subfield: Multimodel QA). Source: MVBench (Li et al., 2024e) and STAR (Wu et al., 2024)

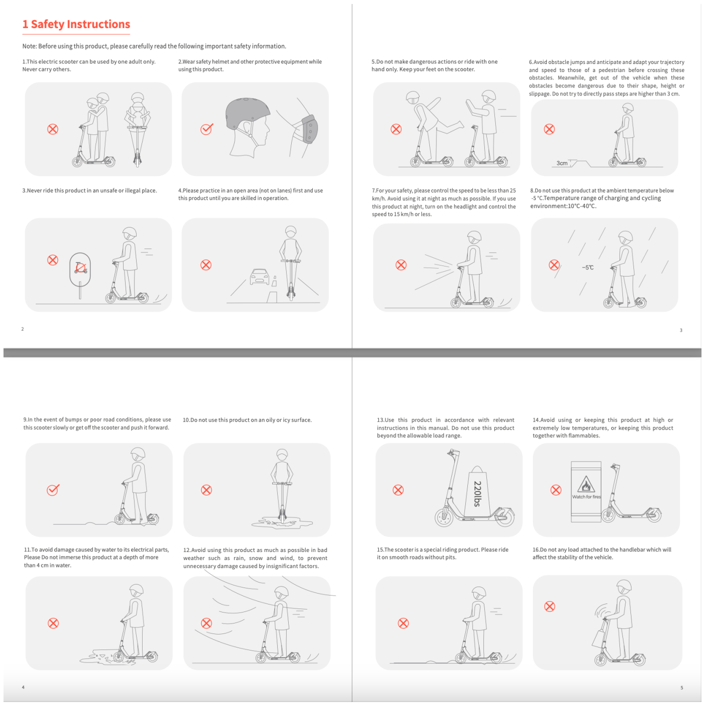
Back to List of Figures

Information Extraction：Detailed Manual Understanding

Task Name: Multi-lingual Manual Explanation Scooter (Chinese)

根据给定的用户手册图片内容，使用中文回答问题。涉及操作上的问题，给出解决方法。涉及人身安全上的问题给出合理建议。
Question: 我骑这个车送孩子上学方便吗？

Keywords: **Document, Open-ended**



1 Safety Instructions

Note: Before using this product, please carefully read the following important safety information.

1.This electric scooter can be used by one adult only. Never carry others.

2.Wear safety helmet and other protective equipment while using this product.

3.Never ride this product in an unsafe or illegal place.

4.Please practice in an open area (not on lanes) first and use this product until you are skilled in operation.

2

5.Do not make dangerous actions or ride with one hand only. Keep your feet on the scooter.

6.Avoid obstacle jumps and anticipate and adapt your trajectory and speed to those of a pedestrian before crossing these obstacles. Meanwhile, get out of the vehicle when these obstacles become dangerous due to their shape, height or slippage. Do not try to directly pass steps are higher than 3 cm.

7.For your safety, please control the speed to be less than 25 km/h. Avoid using it at night as much as possible. If you use this product at night, turn on the headlight and control the speed to 15 km/h or less.

8.Do not use this product at the ambient temperature below -5 °C.Temperature range of charging and cycling environment:10°C-40°C.

3

9.In the event of bumps or poor road conditions, please use this scooter slowly or get off the scooter and push it forward.

10.Do not use this product on an oily or icy surface.

11.To avoid damage caused by water to its electrical parts, Please Do not immerse this product at a depth of more than 4 cm in water.

12.Avoid using this product as much as possible in bad weather such as rain, snow and wind, to prevent unnecessary damage caused by insignificant factors.

4

13.Use this product in accordance with relevant instructions in this manual. Do not use this product beyond the allowable load range.

14.Avoid using or keeping this product at high or extremely low temperatures, or keeping this product together with flammables.

15.The scooter is a special riding product. Please ride it on smooth roads without pits.

16.Do not any load attached to the handlebar which will affect the stability of the vehicle.

5

GPT-4o : Answer: 不建议使用这款滑板车送孩子上学。根据用户手册的安全说明，这款电动滑板车只能由一名成人使用，且不允许载人。此外，手册中明确指出不要进行危险动作或单手骑行，这样会增加安全风险。因此，为了您和孩子的安全，建议选择其他更为安全的交通工具。(score: 0.9)

Error Category: **Perception Error**, **Lack of Knowledge**
Idefics3 :
Answer: 是的，滑板车可以方便地送孩子上学。您可以在孩子上学时使用滑板车，减少交通拥堵和堵车的时间。(score: 0.0)

Reference Answer: **电动滑板车严禁搭载乘客，其设计和承重能力仅适合单人使用。擅自搭载他人，特别是带孩子一起乘坐，不仅违反使用规范，还可能带来严重的安全隐患。出于对自身和孩子安全的考虑，不建议使用滑板车送孩子上学。**

Figure 18: A sample error case of Information Extraction (subfield: Detailed Manual Understanding).Source:Web

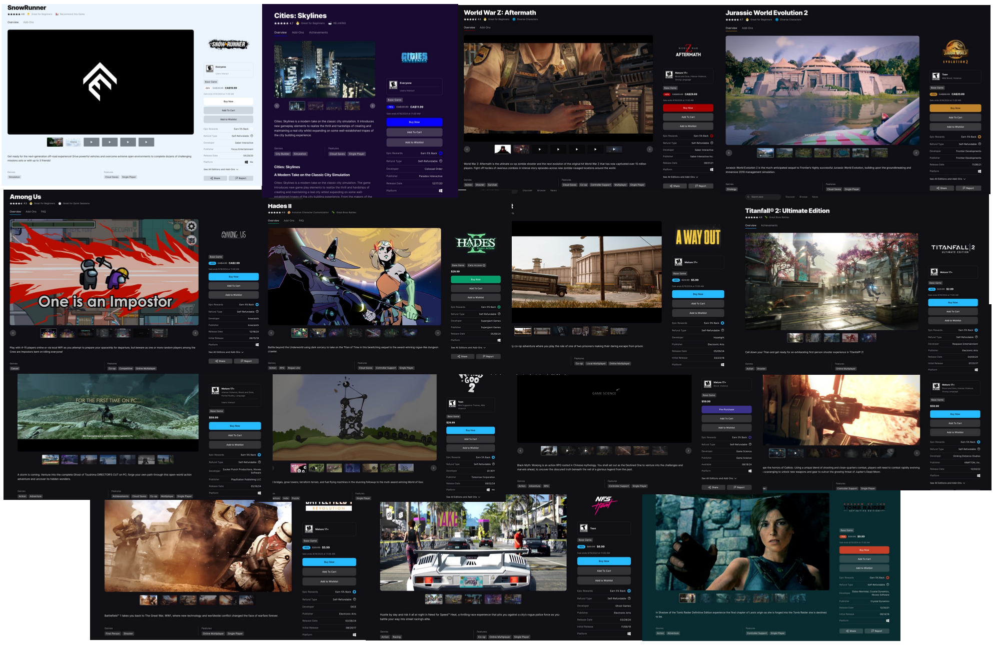
Back to List of Figures

Information Extraction: Search by Attribute without Calculate

Task Name: Game Info Retrieval

Given a set of screenshots from a game information page and a specific query, retrieve the names of the games that match the query. If there are multiple matching games, provide a list of game names separated by commas.
Question: Find the game available on 'MacOS'

Keywords: **Object Recognition and Classification, OCR, Language Understanding and Generation, User Interface Screenshots**



Claude-3.5 : Let's go through this step-by-step:
1. We need to look for a game that specifically mentions Mac or MacOS as a platform. …
Answer: World of Goo 2, SnowRunner (score: 1.0)

Error Category: Perception Error
GPT-4o: To find the game available on 'MacOS', I will examine each screenshot for the platform information.
…
6. World of Goo 2: No mention of MacOS.
…
Answer: SnowRunner(score: 0.0)

Correct Answer: World of Goo 2, SnowRunner

Figure 19: A sample error case of Information Extraction (subfield: Search by Attribute without Calculate).Source:Web

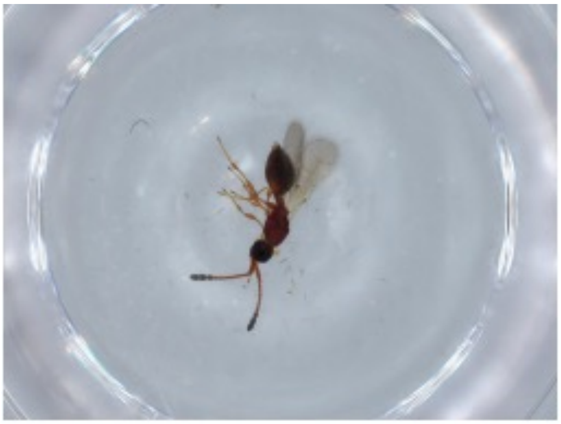
Back to List of Figures

Knowledge: World Knowledge

Task Name: Insect Order Classification

This task involves the classification of insects into their respective taxonomic orders based on visual input. The goal is to accurately identify and categorize an insect from an image into one of the pre-defined orders. Each order is represented by a specific label corresponding to the insect's taxonomic classification, including orders such as Diptera, Hymenoptera, Coleoptera, Hemiptera, Lepidoptera, Psocodea, Thysanoptera, Trichoptera, Orthoptera, Blattodea, Neuroptera, Ephemeroptera, Dermaptera, Archaeognatha, Plecoptera, or Embioptera.

Keywords: **Object Recognition and Classification, Photographs, Domain-Specific Knowledge and Skills, Contextual Formatted**



Error Category: Lack of Knowledge
GPT-4o: 1. The insect has a pair of wings. 2. The antennae are feathery, which is a characteristic feature of some insects. 3. The body structure is relatively small and delicate …
Answer: Trichoptera (score: 0.0)

Error Category: Lack of Knowledge
Claude-3.5: 1. The insect is small and appears to be in a circular container, likely for observation purposes. 2. The insect has an elongated body shape …
Answer: Lepidoptera (score: 0.0)

Error Category: Lack of Knowledge
Gemini-1.5-pro: The insect has long, slender antennae and its wings are held roof-like over its body. These are characteristic of the order Trichoptera, or caddisflies.
Answer: Trichoptera (score: 0.0)

Correct Answer: Hymenoptera

Figure 20: A sample error case of Knowledge (subfield: World Knowledge).
Source: BIOSCAN-1M (Gharaee et al., 2024)

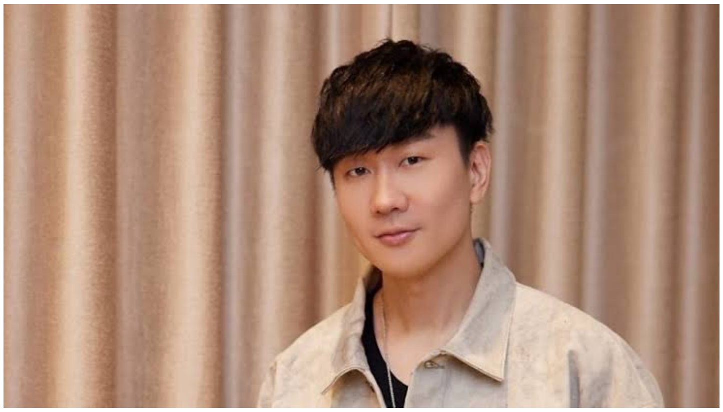
Back to List of Figures

Knowledge: World Knowledge

Task Name: Memorization Chinese Celebrity

Please answer the name and nationality of the celebrity. For the name, please put last name in the front.

Keywords: **Object Recognition and Classification, Photographs, Language Understanding and Generation, Structured**



Error Category: Lack of Knowledge
GPT-4o: I don't know who they are.
Answer: null(score: 0.0)

Error Category: Refuse to Answer
Claude-3.5: I apologize, but I'm not able to identify or name specific individuals in images. However, I can describe what I see in this photo:…
Answer: null(score: 0.0)

Error Category: Lack of Knowledge
Gemini-1.5-pro: The person in the image is Eric Chou. He is a Taiwanese singer.
Answer: {“name”: “Chou Chih-chieh”; “nationality”: “Taiwanese”} (score: 0.0)

Correct Answer: {“name”: “Lin Junjie”; “nationality”: “Singaporean”}

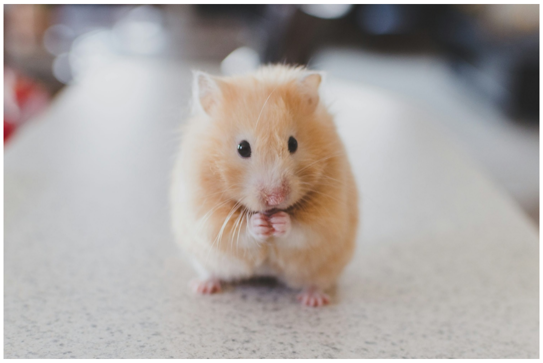
Figure 21: A sample error case of Knowledge (subfield: World Knowledge). Source: Web
Back to List of Figures

Knowledge: Arts

Task Name: Poetry Generation (Acrostic)

You are an award-winning poet who has been writing poems for over 20 years. Please write an acrostic poem about the attached image, using the letters in the specified word or words to start off the first letter of each line in the poem. A space between the words indicates a newline. If there are no spaces, there should not be any blank lines. No title is needed.
Question: Word: hamster

Keywords: **Object Recognition and Classification, Language Understanding and Generation, Photographs**



GPT-4o: Answer:
Huddled in a cozy corner,
A tiny heart beats with gentle grace.
Mischief sparkles in those bright eyes,
Soft fur, a warm embrace.
Tiny paws clutching a hidden treasure,
Eagerly nibbling, lost in pleasure.
Radiating charm, a small wonder. (score: 1.0)

Error Category: Fail to Follow Instruction
Qwen2-VL-72B: Answer:
Humble hamster, with fur so fine,
A creature small, yet full of might.
Majestic in its tiny form,
Standing tall, without a care.
Eyes so bright, a curious gleam,
Ruling its world, in a tiny dream. (score: 0.0) (acrostic: 0, contain: 1)

Eval Context: acrostic: hamster,
contain: [hamster, paw, tail, whisker, seed, rodent, scurry, fur]"

Figure 22: A sample error case of Knowledge (subfield: Art). Source: Web

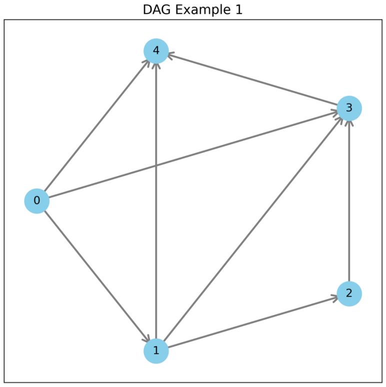
Back to List of Figures

Mathematics: Graph Theory

Task Name: Topological Sort

For a given Directed Acyclic Graph (DAG), your task is to output all possible topological orders. The output is a set of topological order.

Keywords: **Spatial and Temporal Reasoning, Structured, Mathematical and Logical Reasoning, Diagrams and Data Visualizations**


DAG Example 1

Error Category: Lack of Capability
GPT-4o: To determine which 3D object can be formed from the given 2D foldable sheet, we need to visualize how the sheet folds into a 3D shape. Let's analyze the 2D sheet and the 3D options step by step …
Answer: [0->1->2->3->4, 0->1->3->4->2, 0->…] (score: 0.0)

Error Category: Lack of Capability
Claude-3.5: 1. Identify the nodes with no incoming edges (sources):
- Node 0 is the only source in this graph ….

Answer: [0->1->2->3->4,0->1->2->4->3] (score: 0.0)

Error Category: Lack of Capability
Gemini-1.5-pro: We can perform a depth-first search (DFS) from each node with no incoming edges. During the DFS, we maintain a stack to keep track of the visited nodes …
Answer: [0->2->1->4->3, 0->2->1->3->4] (score: 0.0)

Correct Answer: [0->1->2->3->4]

Figure 23: A sample error case of Mathematics (subfield: Graph Theory).
Source:Web

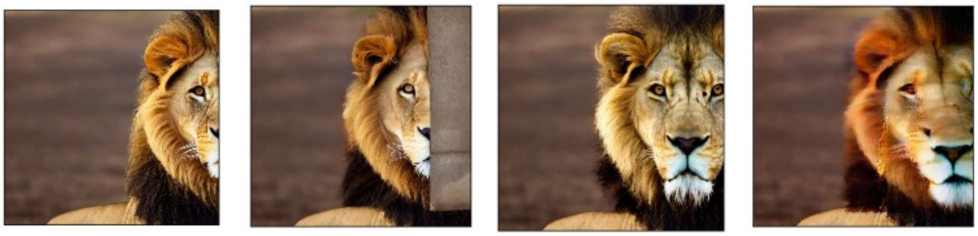
Back to List of Figures

Metrics: Generated Image Eval

Task Name: Autorater Motion Guided Editing

Motion-guided image editing is important for generating realistic and context-aware animation. Your task is to rank the motion-guided image generation results. The desired motion is described by a text input, several generative models try to edit the input image based on the described motion. You should rate the generation results based on 1) how well the generated image follows the motion described by the text query and 2) whether the generated image is still consistent with the source image in terms of semantics and object attributes. The first image is the source image; the rest are the edited results. Rank the results using their indices, starting with 1. Exclude the source image from the ranking.
Question: Move the lion to the left

Keywords: **Object Recognition, Photographs, Spatial and Temporal Reasoning, Structured**



Input image **1** **2** **3**

Claude-3.5: 1. Image 2: Best follows the instruction to move left while maintaining the lion's features and overall composition. 2. Image 3: Maintains consistency with the source image but shows minimal leftward movement. 3. Image 1: Follows the leftward motion but obscures too much …
Answer: 2, 3, 1 (score: 1.0)

Error Category: Fail to Follow Instruction
Idefics3:
Answer: no. (score: 0.0)

Error Category: Fail to Follow Instruction
internvl-76B: The first image shows the lion facing forward, with its head straight. The second image shows the lion tilting its head to the left ... Based on these observations, we can conclude that the second image is the one that shows the lion moving to the left.
Answer: 2 (score: 0.0)

Correct Answer: 2,3,1

Figure 24: A sample error case of Metrics (subfield: Generated Image Eval).
Source:Motion Guidance (Geng & Owens, 2024)

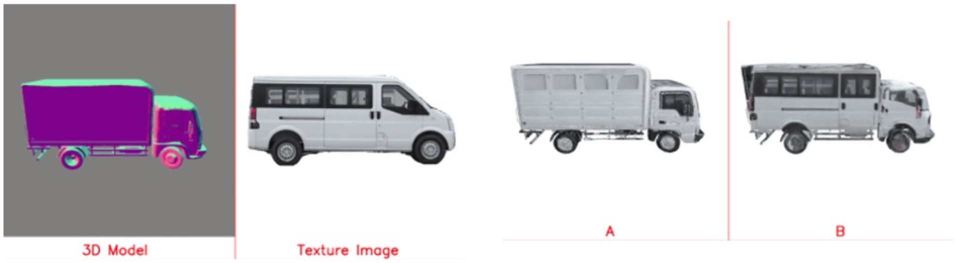
Back to List of Figures

Metrics: Generated Image Eval

Task Name: Autorater 3d Model Texturing

You will be asked to evaluate the quality of textured 3D models by comparing two texture transfer results. The first image will show an untextured 3D model and a source image whose texture needs to be transferred to the mesh. The second image will show two textured 3D models for comparison, and you should pick one with better texturing quality (left or right).

Keywords: **Object Recognition, 3D Models and Aerial Imagery, Scene and Event Understanding, Contextual Formatted Text**



Claude-3.5: Model A doesn't match the source image well. While it's a realistic vehicle, it's a different type (cargo truck instead of passenger van) …
Answer: right (score: 1.0)

Error Category: Perception Error
GPT-4o: To determine which textured 3D model has better texturing quality, we need to consider the realisticness of the textured object and the consistency between the textured mesh and the source image. …
Answer: left (score: 0.0)

Error Category: Perception Error
Gemini-1.5-pro: The left image (A) is a white truck, while the right image (B) is a combination of a truck and a van. The source image is a van. Therefore, the left image is more realistic and consistent with the source image. …
Answer: left (score: 0.0)

Correct Answer: right

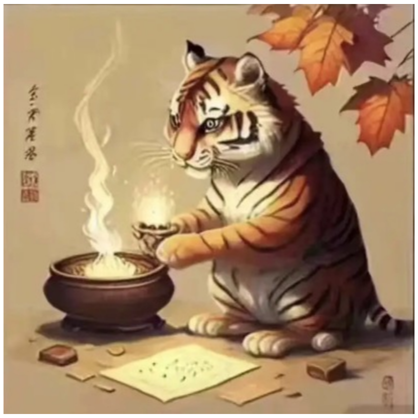
Figure 25: A sample error case of Metrics (subfield: Generated Image Eval).
Source: EASI-Tex (Perla et al., 2024)
Back to List of Figures

Planning: Puzzles and Games

Task Name: Pictionary GenAI Output Chinese

Look at the provided image and question, guess which Chinese word or phrase the image is trying to convey. Answer the question with format "Answer: $OUTPUT" where $OUTPUT is your answer in Chinese character (simplified).
Question:图中表示了一个六字典故，请问是什么？

Keywords: **Object Recognition and Classification, Artistic and Creative Content, Language Understanding and Generation, Contextual Formatted**



Error Category: Lack of Capability
GPT-4o: The image shows a tiger making tea, which is a visual representation of the Chinese idiom "老虎不吃人" (a tiger that doesn't eat people). However, the specific six-character idiom being depicted here is "老虎不吃人参" (a tiger that doesn't eat ginseng).
Answer: 老虎不吃人参 (score: 0.0)

Error Category: Lack of Capability
Claude-3.5: 1. We see a tiger in the image, which is the central figure
...
5. The tiger seems to be focused on or studying the burning incense.
Answer: 卧薪尝胆 (score: 0.0)

Correct Answer: 唐伯虎点秋香

Figure 26: A sample error case of Planning: (subfield: Puzzles and Games).
Source: Web

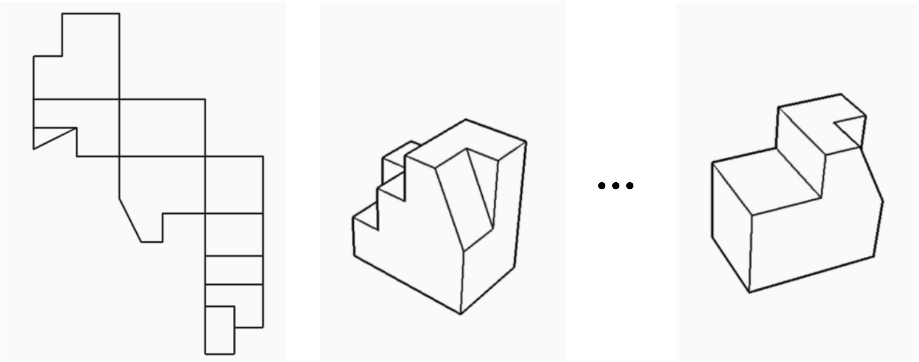
Back to List of Figures

Planning: Puzzles and Games

Task Name: Logical Reasoning 2d Folding

Given the query image including a 2D foldable sheet (the first image) and several options for the folded 3D objects (the remaining images), please find out which 3D object comes from the 2D sheet. The answer should the image index starting from 1 that represents the second image.

Keywords: **Spatial and Temporal Reasoning, Multiple Choice, Mathematical and Logical Reasoning, Diagrams and Data Visualizations**



Error Category: Lack of Capability
GPT-4o: To determine which 3D object can be formed from the given 2D foldable sheet, we need to visualize how the sheet folds into a 3D shape. Let's analyze the 2D sheet and the 3D options step by step …
Answer: 1 (score: 0.0)

Error Category: Lack of Capability
Claude-3.5: 1. First, we need to analyze the 2D foldable sheet (the first image). It has a unique shape with several rectangular sections and one triangular section. 2. Now, let's look at each of the 3D objects (images 1-5) and try to match them with the 2D sheet …
Answer: 1 (score: 0.0)

Error Category: Lack of Capability
Gemini-1.5-pro: The 2D sheet has a long base with a small square attached to the right. There are two protrusions from the base, one with a triangular cutout and one rectangular. Only option 1 satisfies these conditions.
Answer: 1 (score: 0.0)

Correct Answer: 3

Figure 27: A sample error case of Planning (subfield: Puzzles and Games).
Source:Web

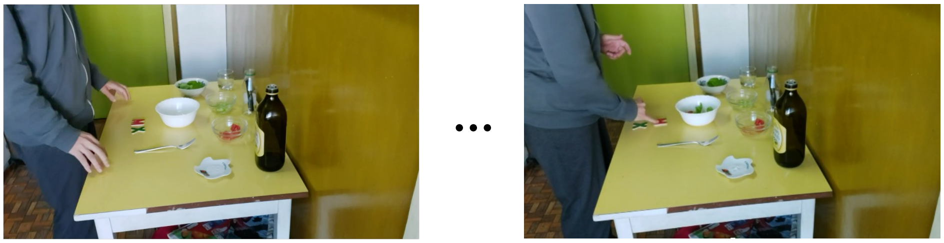
Back to List of Figures

Planning: Reordering

Task Name: Perception Test Video Character Order

The task involves identifying the order of letters as a person writes, types, or arranges them, predicting subsequent letters, and reversing letter sequences in various scenarios. What was the order of the letters at the beginning?

Keywords: **Object Recognition, Video, Spatial and Temporal Reasoning, Contextual Formatted Text**



GPT-4o: The order of the letters at the beginning was M X.
Answer: mx (score: 1.0)

Error Category: Fail to Follow Instruction
Idefics3: The order of the letters at the beginning was not mentioned in the facts provided.
Answer: null (score: 0.0)

Error Category: Perspection Error
Gemini-1.5-pro: The letters at the beginning of the video spell out MIX. The person first places the M, then the I, and finally the X.
Answer: mix (score: 0.0)

Correct Answer: mx

Figure 28: A sample error case of Planning (subfield: Reordering).
Source:Perception Test (Patraucean et al., 2024)

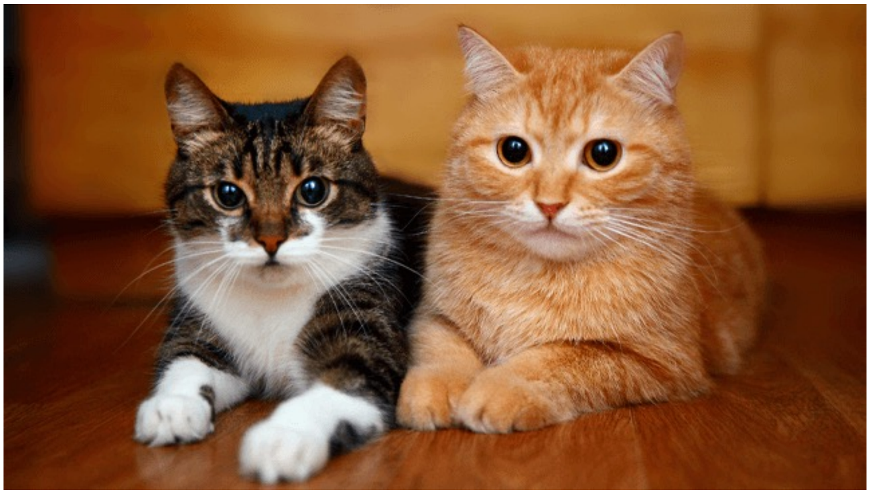
Back to List of Figures

Perception: Multimodal Constrained Captioning

Task Name: Constrained Generation Contain Length

Can you write a story about the animal in the figure with more than 10 but less than 20 words?

Keywords: **Object Recognition and Classification, Open-Ended, Language Understanding and Generation, Photographs**



GPT-4o: Two curious cats, one tabby and one ginger, explored their cozy home, discovering hidden treasures together. (score: 1.0)

Error Category: Fail to Follow Instruction
Claude-3.5: Two feline friends, a tabby and a ginger, lounged side by side, their curious eyes gleaming with mischief and companionship. (score: 0.0) (contain: 0, length1: 1, length2: 0)

Eval Context: contain: [cat, kitten], length1: >10, length2: <20

Figure 29: A sample error case of Perception (subfield: Multimodal Constrained Captioning).
Source: Web

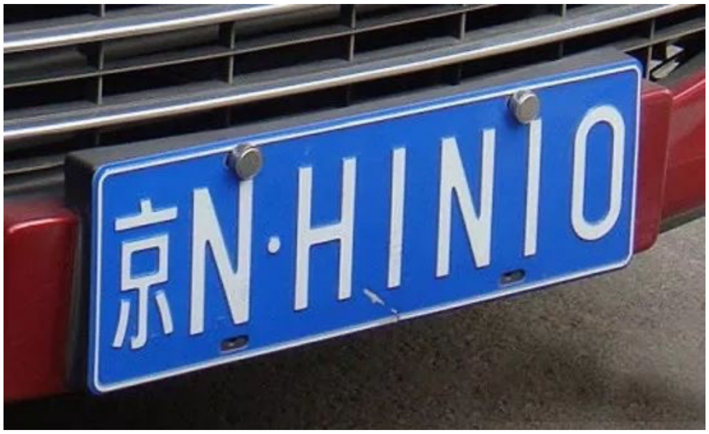
Back to List of Figures

Perception: Visual Recognition

Task Name: License Plate Recognition

Please extract the license plate name from the image, ignore the punctuations.

Keywords: **Text Recognition (OCR), Contextual Formatted Text, Object Recognition and Classification, Photographs**



GPT-4o: 京N ·HINIO
Answer: 京NHINIO (score: 1.0)

Error Category: Lack of Knowledge
Claude-3.5: Let's approach this step-by-step: 1. The image shows a blue license plate, similar to the example provided … The task asks us to ignore punctuation, so we should remove the dot (•). 6. Combining all elements and ignoring punctuation, we get: 京NHIN10.
Answer: 京NHIN10 (score: 0.0)

Error Category: Lack of Knowledge
Gemini-1.5-pro: The license plate in the image contains the characters "京N" followed by "HINI0".
Answer: 京NHINI0 (score: 0.0)

Correct Answer: 京NHINIO

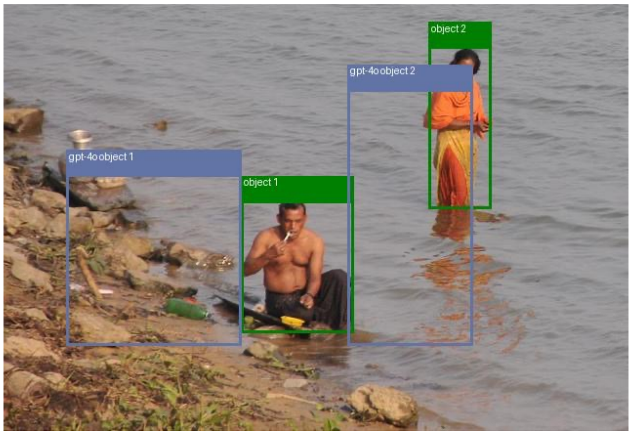
Figure 30: A sample error case of Perception (subfield: Visual Recognition).
Source:Web
Back to List of Figures

Perception: Visual Recognition

Task Name: Coco Person Detection

You are asked to detect persons in a query image. The format of bounding box is (x1,y1,x2,y2), where (x1,y1) is the top-left corner and (x2,y2) is the bottom-right corner. The coordinates are normalized by the image's height and width.

Keywords: **Object Recognition and Classification, Photographs, Numerical Data**



Error Category: Perception Error
GPT-4o: 1. Identify the persons in the image. 2. Determine the bounding boxes for each person. 3. Normalize the coordinates by the image's height and width …
Answer: {"number of person": "2";
"bounding boxes": "[(0.05,0.40,0.30,0.80), (0.60,0.20,0.85,0.80)]"} (score: 0.54)

Error Category: Perception Error
Claude-3.5: 1. I can see two people in the image, both partially submerged in water. 2. The first person is on the left side of the image, sitting in shallow water near the shore. …
Answer: {"number of person": "2";
"bounding boxes": "[(0.20,0.40,0.55,0.95), (0.70,0.15,0.90,0.85)]"} (score: 0.64)

Error Category: Perception Error
Gemini-1.5-pro: There are two people in the image. The man is on the left and the woman is on the right …
Answer: {"number of person": "2";
"bounding boxes": "[(0.42,0.54,0.74,0.84), (0.68,0.52,0.80,0.82)]"} (score: 0.62)

Correct Answer: {"number of person": "2";
"bounding boxes": "[(0.38,0.46,0.56,0.77), (0.68,0.10,0.78,0.48)]"}

Figure 31: A sample error case of Perception (subfield: Visual Recognition).
Source: COCO (Lin et al., 2014)

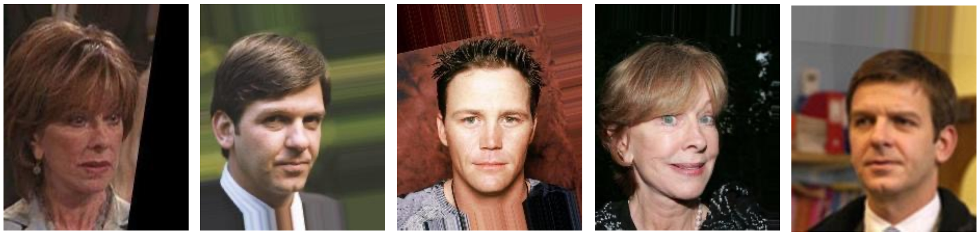
Back to List of Figures

Perception: Visual Recognition

Task Name: Face Identity Matching

This task involves analyzing a set of 5 images to identify which images show the same person. Among the 5 images, there are two pairs of images where each pair shows the same individual, and one image shows a different person. The goal is to determine the matching pairs by providing the indices of the images that depict the same person. The answer should list the smaller indices first within each pair.

Keywords: **Scene and Event Understanding, Object Recognition, Photographs, Contextual Formatted**



Claude-3.5 : 1. The first image shows an older woman with short, brown hair. 2. The second image shows a man with short, dark hair. 3. The third image shows a man with short, light brown hair. 4. The fourth image shows an older woman with short, light brown hair …
Answer: 14,25 (score: 1.0)

Error Category: Fail to Follow Instruction
Idefics3: Example Response: [PLEASE OUTPUT YOUR REASONING]
Answer: 1, 3 (score: 0.0)

Correct Answer: 14,25

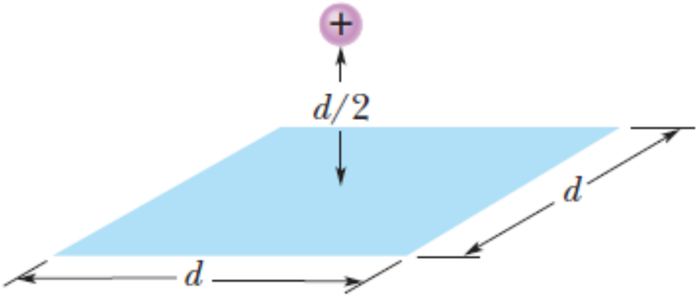
Figure 32: A sample error case of Perception (subfield: Visual Recognition).
Source: CelebA (Liu et al., 2015)
Back to List of Figures

Science: STEM

Task Name: Scibench Fundamental wo Solution

Solve the problem. The answer is a number. A proton is a distance d/2 directly above the center of a square of side d. What is the magnitude of the electric flux through the square? (Hint: Think of the square as one face of a cube with edge d).

Keywords: **Mathematical and Logical Reasoning, Numerical Data, Domain-Specific Knowledge and Skills, Diagrams and Data Visualizations**



Error Category: Lack of Capability
GPT-4o: To solve the problem, we need to determine the electric flux through the square due to the proton positioned at a distance \(d/2 \) directly above the center of the square …
Answer: 3.01 \times 10^{-21} (score: 0.0)

Error Category: Fail to Follow Instruction
Claude-3.5: First, recall Gauss's law for electric fields. It states that the total electric flux through a closed surface is equal to the enclosed charge divided by ε_0 (the permittivity of free space) …
Answer: $|q| / (6\varepsilon_0)$ (score: 0.0)

Error Category: Fail to Follow Instruction
Gemini-1.5-pro: The electric flux through a closed surface is given by Gauss's law: $\Phi_E = \frac{q_{enc}}{\epsilon_0}$...
Answer: $q/(6\epsilon_0)$ (score: 0.0)

Correct Answer: 3.01

Figure 33: A sample error case of Science (subfield: STEM).
Source: SciBench (Wang et al., 2023b)
Back to List of Figures

G DETAILED TASK INFORMATION

In Table 18, we list data source details for every task in our benchmark. We also list the output format and metrics to help better understand each task's form.

Table 18: Detailed task information description of MEGA-BENCH.

Task Name	Source Description	Output Format	Metrics
	Information Extraction		
Cheapest Flight Identification	Screenshots were taken by the human annotator on Google Flights. Questions and answers were created by the annotator.	Contextual	Simple String Match
Weather Info Retrieval	Screenshots were taken by the human annotator on Microsoft Weather. Questions and answers were created by the annotator.	Contextual	String Set Equality Comma
Stock Info Retrieval	Screenshots were taken by the human annotator on Yahoo Finance. Questions and answers were created by the annotator.	Contextual	Set Equality
Game Platform Support Identification	Screenshots were taken by the human annotator on the Steam store. Questions and answers were created by the annotator.	Structured	Exact String Match, Set Equality
Top Rated Hotel Identification	Screenshots were taken by the human annotator on Booking.com. Questions and answers were created by the annotator.	Contextual	String Set Equality Comma
Movie Info Retrieval	Screenshots were taken by the human annotator on the Amazon Prime Video webpage. Questions and answers were created by the annotator.	Contextual	String Set Equality Comma
Top Video Creator Identification	Screenshots were taken by the human annotator on YouTube. Questions and answers were created by the annotator.	Exact	Exact String Match
Highest Discount Game Price Identification	Screenshots were taken by the human annotator on the Steam store. Questions and answers were created by the annotator.	Numerical	Exact String Match
Newspaper Page Parse And Count	Data collected from the Newspaper Navigation Dataset (Lee et al., 2020). Questions and answers were created by the annotator.	Exact	Exact String Match
Remaining Playback Time Calculation	Screenshots were taken by the human annotator on YouTube. Questions and answers were created by the annotator.	Exact	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Multi Lingual Manual Explanation Scooter Spanish	Screenshots taken from user manual located at https://fcc.report/FCC-ID/2A33E5LCHG11U/6288539.pdf. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Multi Lingual Manual Explanation Scooter Arabic	Screenshots taken from user manual located at https://fcc.report/FCC-ID/2A33E5LCHG11U/6288539.pdf. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Multi Lingual Manual Explanation Scooter French	Screenshots taken from user manual located at https://fcc.report/FCC-ID/2A33E5LCHG11U/6288539.pdf. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Multi Lingual Manual Explanation Scooter Chinese	Screenshots taken from user manual located at https://fcc.report/FCC-ID/2A33E5LCHG11U/6288539.pdf. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Multi Lingual Manual Explanation Scooter Russian	Screenshots taken from user manual located at https://fcc.report/FCC-ID/2A33E5LCHG11U/6288539.pdf. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Video Summary	Videos taken from WikiHow or YouTube. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Video Short Title	Videos taken from YouTube. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Video2notes	WikiHow or YouTube. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Video Content Reasoning	Videos and annotations were taken from the HME100k (Yuan et al., 2022) dataset. Questions and answers were adapted by a human annotator.	Contextual	Simple String Match
COCO OOD Global Image Retrieval By Query Property	Images were from COCO-O (Mao et al., 2023). Questions and answers were re-designed by the annotator manually	Structured	Jaccard Index

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Places365 Similar Scene Retrieval	Images and labels were taken from the Places365 dataset (Zhou et al., 2017) and adapted into questions and answers by a human annotator.	MC	Exact String Match
Booking Web Recommendation	Images and labels come from the SEED-Bench (Li et al., 2024b) dataset. Some images are from Yelp. Questions and annotations were adapted by a human annotator.	Contextual	Jaccard Index Case Insensitive
Game Info Retrieval	Screenshots were taken by the human annotator on the Epic Games Store. Questions and answers were created by the annotator.	Contextual	String Set Equality Comma
Media Homepage Profile	Most images and labels come from the SEED-Bench (Li et al., 2024b) dataset, while one came from a screenshot taken by a human annotator. Questions and annotations were adapted by a human annotator.	Structured	Jaccard Index Case Insensitive
Movie Retrieval By Actor	Screenshots were taken by the human annotator on the Amazon Prime Video webpage. Questions and answers were created by the annotator.	Contextual	String Set Equality Comma
Music Info Retrieval	Screenshots were taken by the human annotator on the Spotify Web Player. Questions and answers were created by the annotator.	Contextual	String Set Equality Comma
Tv Show Retrieval By Character	Screenshots were taken by the human annotator on the Amazon Prime Video webpage. Questions and answers were created by the annotator.	Contextual	String Set Equality Comma
App Layout Understanding Leetcode	Screenshots were taken by the human annotator on Leetcode. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Youtube	Screenshots were taken by the human annotator on YouTube. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Amazon	Screenshots were taken by the human annotator on Amazon. Questions and answers were created by the annotator.	Exact	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
App Layout Understanding Word	Screenshots were taken by the human annotator on Microsoft Word. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Notes	Screenshots were taken by the human annotator on the Google Notes app. Questions and answers were created by the annotator.	Exact	Exact Str Match Case Insensitive
App Layout Understanding Ppt	Screenshots were taken by the human annotator on Microsoft PowerPoint. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Alipay	Screenshots were taken by the human annotator on the Alipay app. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Instagram	Screenshots were taken by the human annotator on the Instagram app. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Zoom	Screenshots were taken by the human annotator on Zoom. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Excel	Screenshots were taken by the human annotator on Microsoft Excel. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Iphone Settings	Screenshots were taken by the human annotator on the iPhone. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Tiktok	Screenshots were taken by the human annotator on the TikTok app. Questions and answers were created by the annotator.	Exact	Exact String Match
App Layout Understanding Twitter	Screenshots were taken by the human annotator on the X (formerly Twitter) app. Questions and answers were created by the annotator.	Exact	Exact String Match
Multilingual News Qa	Screenshots were taken by the human annotator on X (formerly Twitter). Questions and answers were created by the annotator.	Contextual	Multi Ref Phrase

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Product Ocr Qa	Images were taken from various websites. Questions and answers were created by the annotator.	Exact	Exact String Match
Research Website Parsing Blogpost	Screenshots were taken of various ML research websites. Questions and answers were created by the annotator.	Contextual	Multi Ref Phrase
Research Website Parsing Homepage	Screenshots were taken of various ML research websites. Questions and answers were created by the annotator.	Contextual	Multi Ref Phrase
Research Website Parsing Publication	Screenshots were taken of various ML research websites. Questions and answers were created by the annotator.	Contextual	Multi Ref Phrase
Gui Chat Easy	Images and annotations were adapted from the GUI Chat dataset (Chen et al., 2024c) by the human annotator into an open-ended question.	Open	GPT-4o as Judge
Gui Chat Hard	Images and annotations were adapted from the GUI Chat dataset (Chen et al., 2024c) by the human annotator into an open-ended question.	Open	GPT-4o as Judge
Realworld Qa En2cn	Images and annotations were adapted from the RealWorldQA benchmark (xAI, 2024) by the human annotator into an open-ended question. The translation requirement was added by the human annotator.	Contextual	Multi Ref Phrase
Star Object Interaction Video	Videos and annotations were adapted from the STAR benchmark (Wu et al., 2024) by the human annotator into questions and answers.	Contextual	Multi Ref Phrase
Funqa Unexpected Action Magic Video	Videos and annotations were adapted from the FunQA benchmark (Xie et al., 2023) by the human annotator into being an open-ended question.	Open	GPT-4o as Judge
Activitynetqa	Images and annotations were adapted from the ActivityNetQA benchmark (Yu et al., 2019) by the human annotator into being an open-ended question.	Open	GPT-4o as Judge

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Funqa Unexpected Action Creative Video	Videos and annotations were adapted from the FunQA benchmark (Xie et al., 2023) by the human annotator into being an open-ended question.	Open	GPT-4o as Judge
Nextqa Mc	Images and annotations were adapted from the NExTQA benchmark (Xiao et al., 2021) by the human annotator into questions and answers.	MC	Exact String Match
Video Qa	Videos taken from YouTube. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Nextqa Oe	Images and annotations were adapted from the NExTQA benchmark (Xiao et al., 2021) by the human annotator into being an open-ended question.	Open	GPT-4o as Judge
Funqa Unexpected Action Humor Video	Videos and annotations were adapted from the FunQA benchmark (Xie et al., 2023) by the human annotator into being an open-ended question.	Open	GPT-4o as Judge
Multilingual Movie Info Parsing	Screenshots were taken by the human annotator on the Amazon Prime Video webpage. Questions and answers were created by the annotator.	Structured	Exact String Match, Simple String Match
Movie Info Parsing	Screenshots were taken by the human annotator on the Amazon Prime Video webpage. Questions and answers were created by the annotator.	Structured	Exact String Match
Stock Info Parsing	Screenshots were taken by the human annotator on Yahoo Finance. Questions and answers were created by the annotator.	Structured	Exact String Match
Music Info Parsing	Screenshots were taken by the human annotator on the Spotify Web Player. Questions and answers were created by the annotator.	Structured	Exact String Match
Multilingual Game Info Parsing	Screenshots were taken by the human annotator on the Epic Games Store. Questions and answers were created by the annotator.	Structured	Exact String Match
Ocr Article Authors	Screenshots taken of various academic papers. Questions and answers created by human annotator.	Structured	Simple String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Youtube Video Info Parsing	Videos taken from YouTube. Questions and answers created by human annnotator.	Structured	Exact String Match
Tv Show Info Parsing	Screenshots were taken by the human annotator on the Amazon Prime Video webpage. Questions and answers were created by the annotator.	Structured	Simple String Match
Ocr Resume School Plain	Resumes taken from various personal websites. Questions and answers were created by the annotator.	Contextual	String Set Equality Line Break
Image Translation En2cn	Images were collected from various sources, including academic papers, news articles, shopping receipts, etc. The annotations are obtained by GPT-4o translation followed by a human check.	Contextual	Gleu Cn
Booking Web Rating	Images and labels come from the SEED-Bench (Li et al., 2024b) dataset. Some images are from Yelp. Questions and annotations were adapted by a human annotator.	Structured	Exact String Match
Weather Info Parsing	Images were collected from the Microsoft Weather by taking screenshots. Questions and answers were designed by the annotator.	Structured	Exact String Match
Game Info Parsing	Screenshots were taken by the human annotator on the Epic Games Store. Questions and answers were created by the annotator.	Structured	Exact String Match
Weather Map Climate Type Temperature Parsing	One of the examples comes from the SEED-Bench 2 Plus benchmark (Li et al., 2024b). The rest of the images were collected from various online websites. Questions and annotations were adapted by a human annotator.	Structured	Exact String Match
Hotel Booking Confirmation Parsing	Screenshots were taken by the human annotator on Booking.com. Questions and answers were created by the annotator.	Structured	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Entertainment Web Game Style	Some of the examples come from the SEED-Bench 2 Plus benchmark (Li et al., 2024b). The rest of the screenshots were taken on the Steam store. Questions and annotations were adapted by a human annotator.	Structured	Exact Str Match Case Insensitive, Exact String Match
Planning			
Wikihow Complex Task Completion	Data collected from website, and the questions and answers are designed by human annotator	Open	GPT-4o as Judge
Vln Identify Robot	Data collected from RxR dataset (Ku et al., 2020), the question and answer are adapted to select the robot that should execute the instruction	Exact	Exact String Match
Vln English Next Step	Data collected from RxR dataset (Ku et al., 2020), the question and answer are adapted by human annotator	Contextual	Simple String Match
Vlnqa Egocentric Navigation Video	Data collected from VLN-CE (Krantz et al., 2020) and the task is adapted from MVBench (Li et al., 2024e), the question and answer are adapted by human annotator	Contextual	Simple String Match
Vln Identify Location	Data collected from RxR dataset (Ku et al., 2020), the question and answer are adapted by human annotator	Structured	Exact String Match
Vln Tegulu Next Step	Data collected from RxR dataset (Ku et al., 2020), the question and answer are adapted by human annotator	Structured	Simple String Match
Vln Hindi Next Step	Data collected from RxR dataset (Ku et al., 2020), the question and answer are adapted by human annotator	Contextual	Simple String Match
App Interactive Operations Instagram	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
App Interactive Operations Leetcode	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Gui Act Web Multi	Data collected from webpage screenshots by human annotator, and the questions and answers bounding boxes are annotated by human annotator	Structured	Exact String Match, Xml Nbbox Iou Single
App Interactive Operations Ppt	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
Gui Act Mobile Swipe	Data collected from application screenshots by human annotator, and the questions and answers bounding boxes are annotated by human annotator	Structured	Xml Norm Point Distance
App Interactive Operations Excel	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
Gui Act Mobile Tap	Data collected from application screenshots by human annotator, and the questions and answers bounding boxes are annotated by human annotator	Numerical	Xml Norm Point In Bbox
App Interactive Operations Alipay	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
Gui Act Web Single	Data collected from webpage screenshots by human annotator, and the questions and answers bounding boxes are annotated by human annotator	Numerical	Xml Nbbox Iou Single
App Interactive Operations Twitter	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
App Interactive Operations Word	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
App Interactive Operations Iphone Settings	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
App Interactive Operations Tiktok	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
App Interactive Operations Notes	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
App Interactive Operations Zoom	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
App Interactive Operations Amazon	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
Web Action Grounding	Data collected from VisualWebBench (Liu et al., 2024a), and the questions and answers are adapted by human annotator	MC	Exact String Match
App Interactive Operations Youtube	Data collected from application screenshots by human annotator, and the questions and answers are designed by human annotator	MC	Exact String Match
Calendar Schedule Suggestion	Data collected from Google Calendar by human annotator, and the questions and answers are designed by human annotator to identify all possible starting times for a meeting within a specified time range and duration	Contextual	Set Equality
Planning Visual Barman	Data collected from Planning Domain Definition Language (PDDL) of Barman, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Visual Floortile	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Visual Storage	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Screenshot Grippers	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Visual Blocksworld	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Planning Screenshot Barman	Data collected from Planning Domain Definition Language (PDDL) of Barman, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Screenshot Termes	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Screenshot Floortile	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Screenshot Blocksworld	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Screenshot Storage	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Visual Termes	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Screenshot Tyreworld	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Planning Visual Grippers	Data collected from website, and the questions and answers are adapted to match the transitions from init state to goal state	Structured	Symbolic Planning Test
Logical Reasoning Find Odd One Out	Data collected from website, and the questions and answers are adapted to match strings	Structured	Dict Equality, Exact String Match
Logical Reasoning Fit Pattern	Data collected from LogicVista (Xiao et al., 2024), and the questions and answers are adapted by human annotator	MC	Exact String Match
Perception-Test Object Shuffle Video	Data collected from VLN-CE (Krantz et al., 2020) and the task is adapted from MVBench (Li et al., 2024e), the question and answer are adapted into single choice by human annotator	MC	Simple String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Chess Puzzles Checkmate	Data collected from Lichess, and the questions and answers are adapted to match strings	Structured	Set Equality
Chess Puzzles Equality	Data collected from Lichess, and the questions and answers are adapted to match strings	Structured	Set Equality
Bridge Strategies Expert	Data and answer are collected from Bridge Master 2000	Open	GPT-4o as Judge
Chess Puzzles Crushing	Data collected from Lichess, and the questions and answers are adapted to match strings	Exact	Exact String Match
Chess Puzzle Single Step	Data collected from Lichess, and the questions and answers are adapted to match strings	Exact	Exact String Match
Chess Find Legal Moves	Data collected from game positions of games in the 2024 FIDE Candidates tournament, and the questions and answers are adapted to match strings	Exact	Chess Move List Jaccard Index, Exact String Match
Bridge Strategies Advanced	Data and answer are collected from Bridge Master 2000	Open	GPT-4o as Judge
Chess Winner Identification	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	Exact	Exact String Match
Bridge Strategies Worldclass	Data and answer are collected from Bridge Master 2000	Open	GPT-4o as Judge
Mahjong	Data collected from website and screenshot of MajSoul, and the answer are annotated by human annotator	Exact	Exact String Match
Chess Sygyzy Endgames	Endgames created by human annotator and data collected from https://syzygy-tables.info, and the questions and answers are adapted to match Jaccard index	Exact	Chess Move List Jaccard Index, Exact String Match
Go Capture Stone	Data collected from https://online-go.com/learn-to-play-go/capture and https://forums.online-go.com/t/capture-go-problems/31531/9, and the questions and answers are adapted to match strings	Exact	Exact String Match
Bongard Problem	Data collected from https://www.oebp.org/welcome.php and https://www.foundalis.com/res/bps/bpidx.htm	Contextual	String Set Equality Comma

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Number Puzzle Kakuro 5x5	Data collected from https://krazydad.com/kakuro/, and the questions and answers are adapted to match strings	Exact	Exact String Match
Mensa Iq Test	Data collected from website, and the questions and answers are adapted to match dict equality	Structured	Dict Equality
Arc Agi	Data collected from https://arcprize.org/play and the task is adapted from Intelligence (Chollet, 2019), the question and answer are adapted into a grid of digits by human annotator	Exact	Exact String Match
Mnist Pattern	Data collected from MNIST (Deng, 2012), and the questions and answers are adapted to match strings	Numerical	Exact String Match
Number Puzzle Sudoku	Data collected from puzzles.ca, and the questions and answers are adapted to match strings	Contextual	Simple String Match
Move Pos To Pos Hanoi 4 Pole	Shortest paths derived from a diagram found on website and the questions and answers are created to match strings and the longest common move prefix	Structured	Exact String Match, Longest Common List Prefix Ratio
Pictionary Cartoon Drawing Guess	Data collected from An early evaluation of gpt-4v (ision) (Wu et al., 2023), the question and answer are adapted to match strings by human annotator	Exact	Exact Str Match Case Insensitive
Pictionary Chinese Food Img2en	Data collected from website, and the questions and answers are adapted to match strings	Exact	Exact Str Match Case Insensitive
Pictionary Doodle Guess	Data collected from website, and the questions and answers are adapted to match strings	Exact	Exact String Match
Pictionary Skribbl Io	Data collected from screenshots collected by human annotator on skribbl.io and the questions and answers are adapted to match strings	Exact	Exact Str Match Case Insensitive
Pictionary Genai Output Chinese	Data collected from screenshot of website, and the questions and answers are adapted to match strings	Exact	Exact String Match
Annoying Word Search	Data collected from various websites, and the answers are annotated by human annotator	Contextual	Dict Jaccard Agg Jaccard

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Logical Reasoning 2d Views Of 3d Shapes	Data collected from website, and the questions and answers are adapted to match strings	Structured	Dict Equality
Maze 2d 8x8	Data generated from https://www.mazegenerator.net/, and the questions and answers are adapted to match strings	Exact	Exact Str Match Case Insensitive
Crossword Mini 5x5	Data collected from website, and the questions and answers are adapted to match strings	Structured	Dict Exact Str Match Agg Recall
Rebus	Data collected from website, and the questions and answers are adapted to match strings	Contextual	Simple String Match
Icon Arithmetic Puzzle	Data collected from An early evaluation of gpt-4v (ision) (Wu et al., 2023), the question and answer are adapted to match strings by human annotator	Structured	Exact String Match, Sequence Equality
Iq Test Open Ended	Data and answers are collected from website	Open	GPT-4o as Judge
Ball Cup Swap 3	Screenshots taken from video and edited together using images found online, and the questions and answers are adapted to match strings	MC	Exact String Match
Logical Reasoning 2d Folding	Data collected from website, and the questions and answers are adapted to match strings	MC	Exact String Match
Perception Test Video Character Order	Data collected from Perception Test (Patraucean et al., 2024) and the task is adapted from MVBench (Li et al., 2024e), the question and answer are adapted into single answer string by human annotator	Contextual	Simple String Match
Comic Page Ordering	Data collected from website	Contextual	Sequence Equality
Recipe Image Ordering	Data collected from website	MC	Sequence Equality
Coding			
Code Translation Easy	Data and test cases are collected from Pintia	Structured	Program Judge
Code Translation Python	Data collected from xCodeEval split (Khan et al., 2023), and test cases are annotated by human	Structured	Program Judge
Code Translation Hard	Data and test cases are collected from Pintia	Structured	Program Judge

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Code Translation Advanced	Data and test cases are collected from Pintia	Structured	Program Judge
Symbolic Graphics Programs Computer Aided Design	Data and answer are collected from SGP-Bench (Qiu et al., 2024)	Contextual	Multi Ref Phrase
Symbolic Graphics Programs Scalable Vector Graphics	Data and answer are collected from SGP-Bench (Qiu et al., 2024)	Contextual	Multi Ref Phrase
Webpage Code Understanding	Data are collected from website, and the question and answer are adapted for string match	MC	Exact String Match
Code Add Tag	Data collected from xCodeEval (Khan et al., 2023), the question and answer are adapted to match code tag	Contextual	Set Equality
Media Recommend Solutions Stackoverflow	Data are collected from Stack Overflow Website, and the question and answer are adapted to match string	MC	Exact String Match
Flowchart Code Generation	Data are collected from website, and the question and answer are designed by human annotator	MC	Exact String Match
Code Solution Compare	Data collected from SGP-Bench (Qiu et al., 2024), and the question and answer are adapted for string match	Exact	Exact String Match
Code Match Problem	Data collected from SGP-Bench (Qiu et al., 2024), and the question and answer are adapted to match code	Exact	Exact String Match
Code Visualization Output Understanding	Data are collected from website, and the question and answer are designed by human annotator	MC	String Set Equality Comma
Code Output Result	Data are collected from SanFoundry MCQs, and the question and answer are designed by human annotator	Exact	Code Result Exact Str Match
Code Execution	Data collected from execution-v2 (Jain et al., 2024a), the question and answer are adapted to match string	Contextual	Simple String Match
Code Retrieval	Data collected from SGP-Bench (Qiu et al., 2024), and the question and answer are adapted to match string	Exact	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Table2latex Complex	Data collected from SGP-Bench (Qiu et al., 2024), and the question and answer are adapted for LLM Judge	Structured	GPT-4o as Judge
Ocr Table To Html	Data are collected from website, and the question and answer are designed by human annotator	Structured	Simple String Match
Ocr Table To Markdown	Data are collected from website, and the question and answer are designed by human annotator	Structured	Simple String Match
Ocr Math Text Latex	Data are collected from website, and the question and answer are designed by human annotator to match text with LaTeX	Contextual	Text With Latex Expr Equality
Ocr Math Equation	Data are collected from website, and the question and answer are designed by human annotator to match LaTeX	Contextual	Latex Expr Equality
Latex Complex Formula Convertion	Data are collected from latex-formulas and TexTeller, and the question and answer are designed by human annotator	Structured	Latex Expr Equality
Ocr Table To Latex	Data are collected from website, and the question and answer are designed by human annotator	Structured	Simple String Match
Ocr Table To Csv	Data are collected from website, and the question and answer are designed by human annotator	Structured	Simple String Match
Code Programming Test Easy	Data and test cases are collected from Pintia	Structured	Program Judge
Code Programming Test Hard	Data and test cases are collected from Pintia	Structured	Program Judge
Code Programming Test Advanced	Data and test cases are collected from Pintia	Structured	Program Judge
Code Programming Extremely Hard	Data and test cases are collected from Pintia	Structured	Program Judge
Visualization With Code	Data are collected from website, and the question and answer are designed by human annotator	Structured	GPT-4o as Judge
Stackoverflow Debug Qa	Data are collected from Stack Overflow Website, and the question and answer are adapted to match string	Structured	Exact Str Match Case Insensitive, Exact String Match
Code Error Line Identification	Data collected from Pintia, and the question and answer are adapted to match string	MC	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Perception			
Visual Correspondence In Two Images	Images are from BLINK (Fu et al., 2024c). Annotator manually added one more reference point per sample and designed structured answers	Structured	Dict Equality
2D Image Jigsaw Puzzle Easy	Images created by playing the online Jigsaw simulator and taking screenshots	Structured	Dict Exact Str Match Agg Recall
Adapted Cvbench Distance	Data collected from CV-Bench's distance split (Tong et al., 2024), and adapted into exact text answer	Exact	Exact String Match
Geometry Plot Position Relationship	Data collected from Internet. Question and answers were designed by the annotator	Exact	Exact String Match
Video Grounding Spatial	Videos collected from VidOR (Shang et al., 2019). Re-designed questions and answers for this specific task	Contextual	Simple String Match
Adapted Cvbench Relation	Data collected from CV-Bench's relation split (Tong et al., 2024), and adapted into exact text answer	Exact	Exact String Match
Egocentric Spatial Reasoning	Data are collected from Epic-Kitchen (Damen et al., 2018) and the Internet. Questions and answers are adapted for contextual formatted output	Contextual	Multi Ref Phrase
Trance Physics Reasoning Basic	Data are collected from Trance (Hong et al., 2023) by specifically picking up samples with the easiest settings. Questions and answers are re-designed for this specific task	Exact	Exact String Match
CLEVER Moving Direction Video	Video data are collected from MVBench (Li et al., 2024e). Questions and answers are adapted for the contextual formatted output format	Contextual	Multi Ref Phrase
Trance Physics Reasoning Event	Data are collected from Trance (Hong et al., 2023) by selecting settings where objects are moved. Questions and answers are re-designed for indicating changed objects	MC	Set Equality
3D Fragments Understanding	We write rendering scripts to produce the data from the assets of the Break Bad dataset (Sellán et al., 2022)	Numerical	Simple String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Physical Property Reasoning	Images are collected from the Internet, questions and answers are designed by annotator	Contextual	Simple String Match
ClEVRER Physics	Images are collected from CLEVRER (Yi et al., 2019), questions and answers are re-designed for testing the understanding of physical status	Numerical	Exact String Match
ClEVRER Video Moving Object Property Recognition	The videos are collected from MVBench (Li et al., 2024e), the questions and answers are adapted to test the understanding of physical property and dynamics	Contextual	Multi Ref Phrase
Trance Physics Reasoning View	Data are collected from Trance (Hong et al., 2023) by selecting the most challenging settings (objects are moved, and two states are captured by different cameras). Questions and answers are re-designed for indicating changed objects	MC	Set Equality
Photoshop Operation	Images are collected from the Web, questions and answers designed by annotator	Structured	Jaccard Index
Relative Reflectance Of Different Regions	Images come from BLINK (Fu et al., 2024c), the annotator added one more point per image and converted the task into a reflectance sorting task	Structured	Sequence Equality
Autonomous Driving Scene Analysis	Images are collected from the Internet, questions and answers are designed by annotator	Exact	Exact Str Match Case Insensitive
Functionality Matching In Different Objects	The images come from BLINK (Fu et al., 2024c). The annotator manually added one ref point per image to augment the task	Structured	Dict Equality
NLVR2 Two Image Compare QA	Images are collected from NLVR2 (Suhr & Artzi, 2019). Questions and answers re-designed by the annotator	MC	Multi Ref Phrase
Egocentric Analysis Single Image	The images are collected from Epic-Kitchens (Damen et al., 2018). Questions and answers are re-designed by the annotator	Exact	Exact String Match Case Insensitive
ClEVR Object Existence Video	Videos are collected from MVBench (Li et al., 2024e). Questions and answers are slightly adapted	MC	Simple String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
SNLI-VE Visual Entailment	Data are collected and converted from SNLI-VE dataset (Xie et al., 2019)	Exact	Exact String Match
OCR Open-ended QA	Images collected from the Internet. Questions and answers made up by the annotator for the open-ended output format	Open	GPT-4o as Judge
Super ClEVR Scene Understanding	Images are collected from SuperCLEVR (Li et al., 2023b). Questions and answers are redesigned by the annotator	Contextual	Multi Ref Phrase
Visual Dialog Image Guessing	Images are collected from Visual Dialog dataset (Das et al., 2017). Questions and answers are designed by the annotator	MC	Exact String Match
Semantic Matching Of Two Images	Images come from BLINK dataset (Fu et al., 2024c). The annotator augmented the data by adding one more ref point and re-designed the answer	Structured	Dict Equality
Recover Masked Word In Figure	The annotator took screenshots from a few public papers on arXiv and designed the question-answer pairs	Contextual	Simple String Match
Graph Interpretation	The images of line/dot graphs are collected from the Internet, and the annotator created the question and open-ended reference answer	Open	GPT-4o as Judge
Science Figure Explanation	The images of science figures are collected from the Internet, and the annotator created the question and open-ended reference answer	Open	GPT-4o as Judge
Bar Chart Interpretation	The images of bar graphs are collected from the Internet, and the annotator created the question and open-ended reference answer	Open	GPT-4o as Judge
Electricity Load Estimate Plot	The temporal data were collected from Informer (Zhou et al., 2021) and AutoFormer (Wu et al., 2021). The annotator re-processed the data to design a more specific task	Numerical	Normalized RMSE
Average Humidity Estimate Plot	The temporal data were collected from AutoFormer (Wu et al., 2021). The annotator re-processed the data to design a more specific task	Numerical	Normalized RMSE

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Exchange Rate Estimate Plot	The temporal data were collected from Lai et al. (2018) and AutoFormer (Wu et al., 2021). The annotator re-processed the data to design a more specific task	Numerical	Normalized Rmse
Road Map Find Highway Between Two Place	The road map images were collected from Seed-Bencn (Li et al., 2024c) and the Internet. Questions and answers are designed by the annotator	Exact	Exact String Match
Transit Map Intersection Points	The transit map images were collected from Seed-Bencn (Li et al., 2024c) and the Internet. Questions and answers are designed by the annotator	Structured	Exact String Match, Sequence Equality Case Insensitive
Panel Images Single Question	Panel images were collected from (Fan et al., 2024). Questions and answers were designed by the annotator	MC	Exact String Match
Knowledge Graph Understanding	The large knowledge graph image was collected from the Internet. Questions and answers were designed by the annotator	Contextual	Set Equality
Panel Images Multi Question	Panel images were collected from (Fan et al., 2024). Questions and answers were designed by the annotator	Structured	Exact String Match
Mindmap Elements Parsing	Mindmap images were collected from Seed-Bencn (Li et al., 2024c) and the Internet. Questions and answers are designed by the annotator	Structured	Set Equality Case Insensitive
Dvqa	Images were collected from Dvqa dataset (Kafle et al., 2018). Questions and answers were re-designed by the annotator	Numerical	Multi Ref Phrase
Figureqa	Images were collected from FigureQA dataset (Kahou et al., 2017). Questions and answers were re-designed by the annotator	MC	Multi Ref Phrase
Map Diagram Qa	Images were collected from MapQA dataset (Chang et al., 2022). Questions and answers were re-designed by the annotator	Contextual	Simple String Match
Chart Vqa	Data were collected from MathVista (Lu et al., 2023) (statistics subset) and converted into a more specific task	Numerical	General Single Numerical Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Photo Sharing Image Retrieval	Images were from the PhotoChat (Zang et al., 2021) dataset. Questions and answers are designed by the annotator	MC	Exact String Match
Multi Load Type Prediction From Plot	The temporal data were collected from Informer (Zhou et al., 2021) and AutoFormer (Wu et al., 2021). The annotator re-processed the data to design a more specific task	MC	Sequence Accuracy Case Insensitive
Stock Price Future Prediction	The annotator downloaded data from Yahoo! Finance's API, and processed data to design this task	Contextual	Normalized Rmse
Traffic Future Prediction From Line Plot	The temporal data were collected from AutoFormer (Wu et al., 2021). The annotator re-processed the data to design a more specific task	Numerical	Normalized Rmse
Electricity Plot Future Prediction	The temporal data were collected from AutoFormer (Wu et al., 2021). The annotator re-processed the data to design a more specific task	Numerical	Normalized Rmse
Ili Ratio Future Prediction	The temporal data were collected from AutoFormer (Wu et al., 2021). The annotator re-processed the data to design a more specific task	Numerical	Normalized Rmse
Paper Vqa	The annotator took high-resolution screenshots of a few papers on arXiv, and designed the questions and answers	Contextual	Simple String Match
Doc Vqa	Data and open-ended QA pairs were converted from DocMatix (HuggingFaceM4, 2024)	Open	GPT-4o as Judge
FunSD Document Qa	Images were collected from FunSD (Jaume et al., 2019). Questions and answers were designed by annotator	Contextual	Simple String Match
OCR Article Journal	The article screenshots were taken from various websites. Questions and answers were created by the annotator	Contextual	Simple String Match
IAM Line Ocr And Locate	Images were collected from the IAM handwritten database (Marti & Bunke, 1999). Questions and answers were re-designed by the annotator	Structured	Exact String Match, Normalized Similarity Damerau Levenshtein

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
OCR Resume Experience Plain	The resume screenshots were taken from various websites. Questions and answers were created by the annotator	Contextual	String Set Equality Line Break
Newspaper Ocr In Query Box	Images were collected from The Newspaper Navigator Dataset (Lee et al., 2020). Questions and answers were adapted by the annotator into simple string answer format.	Contextual	Simple String Match
OCR Resume Skill Plain	The article screenshots were taken from various websites. Questions and answers were created by the annotator	Contextual	String Set Equality Line Break
OCR Resume Employer Plain	The article screenshots were taken from various websites. Questions and answers were created by the annotator	Contextual	String Set Equality Line Break
Finance Table Understanding	Images were collected from MMMU (Yue et al., 2024a). Questions and answers were adapted by the annotator into direct numerical output format	Numerical	Exact String Match
Monthly Weather Days Count	Images were collected from the Microsoft Weather by taking screenshots. Questions and answers were designed by the annotator.	Structured	Exact String Match
Table Understanding Complex Question Answering	Tables were collected from WikiTableQuestions (Pasupat & Liang, 2015) and TabFact (Chen et al., 2019). Questions and answers were designed by the annotator	Contextual	Simple String Match
Table Understanding Fetaqa	Data were collected and converted from FetaQA (Nan et al., 2022)	Open	GPT-4o as Judge
Table Understanding Fact Verification	Tables were collected from WikiTableQuestions (Pasupat & Liang, 2015) and TabFact (Chen et al., 2019). Questions and answers were designed by the annotator	Contextual	Dict Precision
Electricity Future Prediction From Table	The temporal data were collected from AutoFormer (Wu et al., 2021). The annotator reprocessed the data to design a more specific task	Numerical	Normalized Rmse

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Video Detail Description	Video and description data were collected from VideoDetailCaption (Maaz et al., 2023) and converted into a specific task	Open	GPT-4o as Judge
Guess Image Generation Prompt	Examples were collected from various online text-to-image generation demos	Open	GPT-4o as Judge
Docci Image Description Long	Data were collected from DOCCI (Onoe et al., 2024)	Open	GPT-4o as Judge
Tweets Captioning	The annotator collected the data from X by taking screenshots and and the texts	Open	GPT-4o as Judge
Image Captioning With Additional Requirements	Images were collected from various sources on the Web. The annotator used Claude 3.5 Sonnet to generate reference answers and manually polished them	Open	GPT-4o as Judge
Ad Count Detection	Image were collected from various websites by taking screenshots. Questions and answers created by the annotator	Numerical	Exact String Match
Adapted Cvbench Count	Data were collected from CV-Bench's counting split (Tong et al., 2024) and adapted into a specific task by rewriting the question-answer pairs	Numerical	Exact String Match
Av Vehicle Multiview Counting	Images were collected from the nuScenes (Caesar et al., 2020) dataset. The annotator designed the questions and implemented a script to generate the answers from the raw annotation	Numerical	Exact String Match
Counting Multi Image	Data were collected from Mantis (Jiang et al., 2024a) and adapted into direct numerical answer	Numerical	Exact String Match
Av Human Multiview Counting	Images were collected from the nuScenes (Caesar et al., 2020) dataset. The annotator designed the questions and implemented a script to generate the answers from the raw annotation	Numerical	Exact String Match
Shape Composition Shapes	Images were made by the annotator using Canva. Questions and answers were created by the annotator	Structured	Positive Int Match
Counting Single Image	Data were collected from Mantis (Jiang et al., 2024a) and adapted into direct numerical answer	Numerical	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
CLEVRER Video Moving Object Count	Video data are collected from MVBench (Li et al., 2024e). Questions and answers are adapted for the direct numerical output	Numerical	Exact String Match
Shape Composition Colours	Images were created by the annotator using Canva. Questions and answers were created by the annotator	Structured	Positive Int Match
Face Identity Matching	Images were collected from CelebA (Liu et al., 2015). Questions and answers re-designed by the annotator for this specific task	Numerical	Set Equality
Rocks Samples Identify	Images, questions, and answers were collected from the Web by the annotator	Contextual	Simple String Match
Animal Pose Estimation	Images were collected from AP-10K (Yu et al., 2021). The annotator implemented a script to produce the answer from raw annotations for this task	Numerical	Sequence Coords Similarity
License Plate Recognition	Images were collected from the Web. Questions and answers were created by the annotator	Exact	Exact Str Match Case Insensitive
Image Style Recognition	Images were collected from the Web. Questions and answers were created by the annotator	Exact	Exact Str Match Case Insensitive
Long String Letter Recognition	Data were designed by the annotator and generated automatically with code	Exact	Exact String Match
COCO Object Detection By Query Property	Images were from MS-COCO (Lin et al., 2014). Questions and answers were re-designed by the annotator and adapted manually	Numerical	Exact String Match, Nbbox Iou Tuple
Widerface Face Count And Event Classification	Images were collected from WiderFace (Yang et al., 2016). Questions and answers were designed and produced by the annotator	Structured	Exact String Match, Simple String Match
Handwritten Math Expression Extraction	Data were collected from HME100K (Yuan et al., 2022)	Contextual	Latex Expr Equality
Geometry Reasoning Circled Letter	Image were collected from Rahmanzadehgervi et al. (2024) are manually created. Questions and answers were re-designed by the annotator	Structured	Exact String Match, Sequence Equality

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Av Multicamera Tracking Predict Bbox	Images were collected from the nuScenes (Caesar et al., 2020) dataset. The annotator designed the questions and implemented a script to generate the answers from the raw annotation	Numerical	Nbbox Iou Sequence
ASCII Art Understanding	Data and annotations were collected and created by the annotator from various online resources	MC	Exact String Match
Face Keypoint Detection	Raw data were from CelebA (Liu et al., 2015). The annotator wrote a script to produce the answers for this task	Structured	Sequence Coords Similarity
Extract Webpage Headline	Images were collected from VisualWebBench (Liu et al., 2024a). Questions and answers were adapted by the annotator	Contextual	Simple String Match
Waldo	Images and annotations were collected and created by the annotator using various resources on the Web	Structured	Dict Nbbox Iou Tuple Agg Jaccard
Geographic Remote Sensing Land Cover	Images and annotations were collected and converted from SATIN (Roberts et al., 2023)	Contextual	Sequence Equality
Signboard Identification	Images were collected from the Internet. The annotator created the question-answer pairs	Contextual	Simple String Match
Long String Number Recognition	Data were designed by the annotator and generated automatically with code	Exact	Exact String Match
Waybill Number Sequence Extraction	Images were collected from the Internet. The annotator created the question-answer pairs	Contextual	Simple String Match
Single Person Pose Estimation	hello, this is Source Description	Structured	Sequence Coords Similarity
COCO Person Detection	Images were from MS-COCO (Lin et al., 2014). Questions and answers were re-designed by the annotator and adapted with a script	Numerical	Exact String Match, Nbbox Iou Tuple
Places365 Scene Type Classification	Images were collected from Places365 (Zhou et al., 2017). Questions and answers were re-designed and generated by the annotator	Exact	Exact String Match
Visual Prediction Rater Openable Part Segmentation	Images were collected using screenshots from arXiv papers' qualitative results. Questions and answers were created by the annotator	MC	Sequence Equality

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Visual Prediction Rater Panoptic Segmentation	Images were collected using screenshots from qualitative results from the arXiv papers. Questions and answers were created by the annotator	MC	Sequence Accuracy Case Insensitive
Visual Prediction Rater Semantic Segmentation	Images were collected using screenshots from the qualitative results of the arXiv papers. Questions and answers were created by the annotator	MC	Sequence Accuracy Case Insensitive
Video To Camera Trajectory Retrieval	Data were collected from the project page of VD3D (Bahmani et al., 2024). Questions and answers designed and created by the annotator	MC	Exact String Match
Sceneqa Scene Transition Video	Video data are collected from MVBench (Li et al., 2024e). Questions and answers are adapted by the annotator into open-ended format	Open	GPT-4o as Judge
Video Segments Reordering	Raw data come from UCF101 (Soomro et al., 2012). The annotator designed the task and re-organized the data to produce the question-answer pairs	Structured	Sequence Equality
Action Sequence Understanding	Data were collected from MileBench (Song et al., 2024). Questions and answers were designed and created by the annotator	Exact	Exact String Match
Video Action Recognition	Raw data come from UCF101 (Soomro et al., 2012). The annotator designed the task and re-organized the data to produce the question-answer pairs	Structured	Exact String Match
Google Streetview Line Sorting	The data were taken from Google Maps. Questions and answers were created by the annotator	Structured	Sequence Equality
Next Action Prediction	Data were collected from MileBench (Song et al., 2024). Questions and answers were designed and created by the annotator	MC	Exact String Match
Perception Test Video Action Count	Video data are collected from MVBench (Li et al., 2024e). Questions and answers are adapted by the annotator into direct numerical output format	Numerical	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Google Streetview Line Reasoning	The data were taken from Google Maps. Questions and answers were created by the annotator	MC	Simple String Match
Video Camera Motion Description	Videos were collected from VidOR (Shang et al., 2019). Questions and answers re-designed and created by the annotator	Exact	Exact String Match
Video Grounding Temporal	Videos were collected from VidOR (Shang et al., 2019). Questions and answers re-designed and created by the annotator	MC	Simple String Match
Web Action Prediction	Data were collected from VisualWebBench (Liu et al., 2024a)	MC	Exact String Match
Cam Traj To Video Selection	Data were collected from the project page of VD3D (Bahmani et al., 2024). Questions and answers designed and created by the annotator	Contextual	Simple String Match
Sta Action Localization Video	Video data are collected from MVBench (Li et al., 2024e). Questions and answers are repurposed for the contextual formatted output format	Contextual	Simple String Match
Contain Contain Images	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Contain Repeat Length	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Multi Contain Repeat Position Only Length	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Contain Length	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Contain Position Images	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Contain Position Length	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Xor Images	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Multi Contain Repeat	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Contain Contain Length	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Multi Contain Position Only	Images were collected from the Web. Questions and constraints are designed by the annotator. This task has no reference answer	Open	Constrained Generation
Relative Depth Of Different Points	Images were collected from BLINK (Fu et al., 2024c). The annotator augmented each sample by adding one more reference point manually and adjusted the answers	MC	Exact String Match
Visual Prediction Rater Depth Estimation	Images were collected by taking screenshots from depth estimation papers on arXiv. Questions and answers were created by the annotator	MC	Sequence Accuracy Case Insensitive
Visual Prediction Rater Novel View Synthesis	Images were collected by taking screenshots from novel view synthesis papers on arXiv. Questions and answers were created by the annotator	MC	Sequence Equality
Pokemon 3d Recognition	Images were created by the annotator from the Pokemon Go game. Questions and answers were designed by the annotator	Structured	Exact String Match
Av View Identification	Images were collected from the nuScenes (Caesar et al., 2020) dataset. Questions and answers were designed and created by the annotator	Contextual	Sequence Accuracy Case Insensitive

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Multiview Reasoning Camera Moving	Images were collected from BLINK (Fu et al., 2024c). Questions and answers were re-designed and augmented by the annotator	Exact	Exact String Match
3d Indoor Scene Text Bbox Prediction	The data is adapted from Multi3DRefer (Zhang et al., 2023). Questions and answers were designed by the annotator and dataset annotation.	Numerical	Nbbox Iou Single
Google Streetview Circle Reasoning	The data were taken from Google Maps. Questions and answers were created by the annotator	MC	Simple String Match
Google Streetview Direction Understanding	The data were taken from Google StreetView. Questions and answers were created by the annotator	Exact	Exact String Match
Video Motion Matching Real 3d	Videos were collected from the project page of Shen et al. (2024). Questions and answers were created by the annotator	MC	Exact String Match
Video Motion Matching 3d Real	Videos were collected from the project page of Shen et al. (2024). Questions and answers were created by the annotator	MC	Exact String Match
Visual Prediction Rater 3d Assembled Quality Understanding	Data were collected from the project page of Wang et al. (2024e). Questions and answers were designed and created by the annotator	MC	Sequence Equality
Visual Prediction Rater Surface Normal Estimation	Images were collected by taking screenshots from surface normal estimation papers on arXiv. Questions and answers were created by the annotator	MC	Sequence Accuracy Case Insensitive
Adapted Cvbench Depth	Images were collected from CV-Bench (Tong et al., 2024). Answers were adapted by the annotator into exact text	Exact	Exact String Match
Visual Prediction Rater Plane Segmentation	Images were collected by taking screenshots from plane segmentation papers on arXiv	MC	Sequence Accuracy Case Insensitive
3d Indoor Scene Text Bbox Selection	Images were collected by taking screenshots from 3D scene understanding papers on arXiv. Questions and answers were designed and generated by the annotator	MC	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Google Streetview Circle Sorting	The data were taken from Google Maps. Questions and answers were created by the annotator	Structured	Sequence Equality
Metrics			
Paper Review Writing	Data collected from OpenReview's public paper reviews	Open	GPT-4o as Judge
Paper Review Rating	Data collected from OpenReview's public paper reviews	Numerical	Number Rel Diff Ratio
Paper Review Acceptance	Data collected from OpenReview's public paper reviews	Exact	Exact String Match
Autorater Artifact	Images were collected from ImagenHub (Ku et al., 2023). Questions and answers adapted by the annotator	MC	Exact String Match
Autorater Control	Images were collected from ImagenHub (Ku et al., 2023). Questions and answers adapted by the annotator	Exact	Exact String Match
Autorater Artifact Reason	Images were collected from ImagenHub (Ku et al., 2023). The annotator created open-ended reference answer manually	Open	Constrained Generation
Autorater Aesthetics	Images were collected from ImagenHub (Ku et al., 2023). Questions and answers adapted by the annotator	Exact	Exact String Match
Autorater Unmask	Images were collected from ImagenHub (Ku et al., 2023). Questions and answers adapted by the annotator	Exact	Exact String Match
Autorater Subject	Images were collected from ImagenHub (Ku et al., 2023). Questions and answers adapted by the annotator	Exact	Exact String Match
Autorater 3d Model Texturing	Resources are collected from the user study of Perla et al. (2024). Questions and answers were designed and created by the annotator	Contextual	Sequence Equality
Autorater Semantics	Images were collected from ImagenHub (Ku et al., 2023). Questions and answers adapted by the annotator	Exact	Exact String Match
Autorater Motion Guided Editing	Images were collected by taking screenshots from image generation papers on arXiv	MC	Sequence Equality

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Autorater Mask	Images were collected from ImagenHub (Ku et al., 2023). Questions and answers adapted by the annotator	Exact	Exact String Match
Video Eval Visual Pref	Video frames were collected from ImagenHub (He et al., 2024). Questions and answers adapted by the annotator	MC	Exact String Match
Generated Video Artifacts	Videos were collected by running various text-to-video diffusion models online. Open-ended reference answers were written by the annotator manually	Open	GPT-4o as Judge
Video Eval Factual Pref	Video frames were collected from ImagenHub (He et al., 2024). Questions and answers adapted by the annotator	MC	Exact String Match
Video Eval Dynamic Pref	Video frames were collected from ImagenHub (He et al., 2024). Questions and answers adapted by the annotator	MC	Exact String Match
Vizwiz Quality Accessment For Blind	Images were collected from Chiu et al. (2020). Questions and answers were adapted and redesigned by the annotator	Contextual	Set Equality
Reward Models T2i Reward	Images were collected from RLAIF-V dataset (Yu et al., 2024a). Questions and answers were adapted by the annotator	Exact	Exact String Match
Reward Models I2t Reward	Images were collected from RLAIF-V dataset (Yu et al., 2024a). Questions and answers were adapted by the annotator	Exact	Exact String Match
Science			
Biology Exams V	Data collected from EXAMS-V (Das et al., 2024) and MMMU-Pro (Yue et al., 2024b), and the questions and answers are adapted to match strings	Contextual	Simple String Match
Pmc Vqa Medical Image Qa	Data collected from NLVR2 dataset (Suhr et al., 2018), and the questions and answers are adapted to match strings	Contextual	Simple String Match
Medical Content Based Retrieval Radiology	Data collected from ROCO dataset (Pelka et al., 2018), and the questions and answers are adapted to match strings	MC	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Medical Abdomen MRI Organ Recognition	Data collected from GMAI-MMBench (Chen et al., 2024b), and the questions and answers are adapted to match sequence accuracy	Contextual	Sequence Accuracy Case Insensitive
Medical Multi Organ Segmentation Rater	Data collected from pdf screenshot, and the questions and answers are adapted to match strings	MC	Exact String Match
Medical Cell Recognition	Data collected from GMAI-MMBench (Chen et al., 2024b), and the questions and answers are adapted to match strings	Exact	Exact String Match
Medical Image Artifacts Indentification	Data collected from GMAI-MMBench (Chen et al., 2024b), and the questions and answers are adapted to match strings	Exact	Exact String Match
Medical Blood Vessels Recognition	Data collected from GMAI-MMBench (Chen et al., 2024b), and the questions and answers are adapted to match strings	Structured	Exact String Match
Healthcare Info Judgement	Data collected from GMAI-MMBench (Chen et al., 2024b), and the questions and answers are adapted to match strings	MC	Exact String Match
Electrocardiogram	Data collected from MMMU (Yue et al., 2024a), and the answers are open-ended	Open	GPT-4o as Judge
Medical Polyp Segmentation Single Object Rater	Data collected from pdf screenshot, and the questions and answers are adapted to match sequence equality	Structured	Sequence Equality
Medical Abdomen Endscopy Organ Recognition	Data collected from GMAI-MMBench (Chen et al., 2024b), and the questions and answers are adapted to match sequence accuracy	Contextual	Sequence Accuracy Case Insensitive
Medical Keywords Based Retrieval Non Radiology	Data collected from ROCO dataset (Pelka et al., 2018), and the questions and answers are adapted to match strings	Exact	Exact String Match
Medical Parasite Detection	Data collected from pdf screenshot, and the questions and answers are adapted to match set equality	Structured	Set Equality
Medical Retrieval Given Surgeon Activity	Data collected from GMAI-MMBench (Chen et al., 2024b), and the questions and answers are adapted to match strings	MC	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Medical Counting Lymphocytes	Data collected from GMAI-MMBench (Chen et al., 2024b), and the questions and answers are adapted to match strings	Numerical	Exact String Match
Chemistry Exams V	Data collected from EXAMS-V (Das et al., 2024) and MMMU-Pro (Yue et al., 2024b), and the questions and answers are adapted to match strings	MC	Simple String Match
Science Molecule Chemistry	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	Contextual	Simple String Match
Mmmu Pro Exam Screenshot	Data collected from MMMU-Pro (Yue et al., 2024b), and the questions and answers are adapted to match strings	MC	Exact String Match
Scibench W Solution Open Ended	Data collected from Scibench (Wang et al., 2023b), and the answers are open-ended	Open	GPT-4o as Judge, General Single Numerical Match
arXiv Vqa	Data collected from screenshots by human annotator, and the questions and answers are adapted to match strings	MC	Exact String Match
Tqa Textbook Qa	Data collected from Dvqa (Kafle et al., 2018), and the questions and answers are refractered from the original TQA dataset	Contextual	Multi Ref Phrase
Question Solution Solving	Data collected from webpage screenshots by human annotator	Contextual	General Single Numerical Match
Quizlet Question Solving	Data collected from webpage screenshots by human annotator	Contextual	General Single Numerical Match
Scibench Fundamental Wo Solution	Data collected from Scibench (Wang et al., 2023b)	Numerical	General Single Numerical Match
Mmmu Physics Chemistry Mcq	Data collected from MMMU (Yue et al., 2024a), and the questions and answers are adapted to match strings	Exact	Exact String Match
Circuit Diagram Understanding	Data collected from webpage screenshots by human annotator	Numerical	Exact String Match
Science Basic Physics	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	Contextual	Simple String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Physics Exams V	Data collected from EXAMS-V (Das et al., 2024) and MMMU-Pro (Yue et al., 2024b), and the questions and answers are adapted to match strings	Contextual	Simple String Match
Knowledge			
Background Change	Images and labels come from the MFCBench (Wang et al., 2024c) dataset. Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Out Of Context	Images and labels come from the MFCBench (Wang et al., 2024c) dataset. Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Text Entity Replace	Images and labels come from the MFCBench (Wang et al., 2024c) dataset. Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Text Style	Images and labels come from the MFCBench (Wang et al., 2024c) dataset. Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Face Attribute Edit	Images and labels come from the MFCBench (Wang et al., 2024c) dataset. Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Face Swap	Images and labels come from the MFCBench (Wang et al., 2024c) dataset. Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Interpret Force Perspective Illusion	Images come from various websites. Questions and annotations were created by a human annotator.	Exact	Exact String Match
Clip Stable Diffusion Generate	Images and labels come from the MFCBench (Wang et al., 2024c) dataset. Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Unusual Images	Images come from various websites. Questions and annotations were created by a human annotator.	Open	GPT-4o as Judge

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Forensic Detection Of Different Images	Images and labels come from the BLINK benchmark (Fu et al., 2024c). Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Veracity	Images and labels come from the MFCBench (Wang et al., 2024c) dataset. Questions and annotations were adapted by a human annotator.	MC	Exact String Match
Distinguish AI Generated Image	Images come from various websites and image generators. Questions and annotations were created by a human annotator.	Exact	Exact String Match
Cultural Vqa	Images and labels come from the CulturalVQA benchmark (Romero et al., 2024). Questions and annotations were adapted by a human annotator.	Contextual	Multi Ref Phrase
Human Relationship Reasoning	Images come from various websites. Questions and annotations were created by a human annotator.	Contextual	Simple String Match
Sign Language	Videos come from Dr. Bill Vicars' "Signs" YouTube channel. Questions and annotations were created by a human annotator.	Contextual	Multi Ref Phrase
Ishihara Test	Images come from various websites. Questions and annotations were created by a human annotator.	Structured	Set Precision
Llavaguard	Images and labels come from the LlavaGuard benchmark (Helff et al., 2024). Questions were created by a human annotator.	Structured	Exact String Match
Red Teaming Racial	Images and labels come from the Red Teaming benchmark (Li et al., 2024f). Questions were created by a human annotator or generated by GPT-4.	Open	GPT-4o as Judge
Red Teaming Captcha	Images and labels come from the Red Teaming benchmark (Li et al., 2024f). Questions were created by a human annotator or generated by GPT-4.	Open	GPT-4o as Judge
Red Teaming Politics	Images and labels come from the Red Teaming benchmark (Li et al., 2024f). Questions were created by a human annotator or generated by GPT-4.	Open	GPT-4o as Judge

Table 18 – continued from previous page

Task Name	**Source Description**	**Output Format**	**Metrics**
Mmsoc Hatefulmemes	Images and labels come from the MMSoc benchmark (Jin et al., 2024). Questions and answers were adapted by a human annotator.	MC	Exact String Match
Red Teaming Visual Order B	Images and labels come from the Red Teaming benchmark (Li et al., 2024f). Questions were created by a human annotator or generated by GPT-4.	Open	GPT-4o as Judge
Red Teaming Celebrity	Images and labels come from the Red Teaming benchmark (Li et al., 2024f). Questions were created by a human annotator. or generated by GPT-4	Open	GPT-4o as Judge
Mmsoc Memotion	Images and labels come from the MMSoc benchmark (Jin et al., 2024). Questions and answers were adapted by a human annotator.	Structured	Exact String Match
Mmsoc Misinformation Politifact	Images and labels come from the MMSoc benchmark (Jin et al., 2024). Questions and answers were adapted by a human annotator.	MC	Exact String Match
Red Teaming Jailbreak	Images and labels come from the Red Teaming benchmark (Li et al., 2024f). Questions were created by a human annotator or generated by GPT-4.	Open	GPT-4o as Judge
Red Teaming Visual Order A	Images and labels come from the Red Teaming benchmark (Li et al., 2024f). Questions were created by a human annotator or generated by GPT-4.	Open	GPT-4o as Judge
Mmsoc Misinformation Gossipcop	Images and labels come from the MMSoc benchmark (Jin et al., 2024). Questions and answers were adapted by a human annotator.	MC	Exact String Match
Red Teaming Visualmisleading	Images and labels come from the Red Teaming benchmark (Li et al., 2024f). Questions were created by a human annotator.	Open	GPT-4o as Judge
Video Content Follow Up	Videos taken from YouTube. Questions and answers created by human annnotator.	Open	GPT-4o as Judge
Meme Explain	Images come from various websites. Questions were created by a human annotator.	Open	GPT-4o as Judge

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Funny Image Title	Images come from various websites. Questions were created by a human annotator.	Open	GPT-4o as Judge
Emotion Recognition	Videos and labels come from the CAER dataset (Lee et al., 2019). Questions and answers were adapted by a human annotator.	Exact	Exact String Match
Image Humor Understanding	Images come from various websites. Questions were created by a human annotator.	Open	GPT-4o as Judge
Humor Explanation	Images and labels come from a Humor Understanding benchmark derived from the New Yorker Caption Contest (Hessel et al., 2022). Questions were created by a human annotator.	Open	GPT-4o as Judge
Mvsa Sentiment Classification	Images and labels come from the MVSA dataset (Niu et al., 2016). Questions and answers were adapted by a human annotator	MC	Exact String Match
Video Intent Recognition	Video and labels come from the MIntRec dataset (Zhang et al., 2022). Questions and answers were adapted by a human annotator.	Contextual	Simple String Match
Humor Understand Caption Match	Images and labels come from a Humor Understanding benchmark derived from the New Yorker Caption Contest (Hessel et al., 2022). Questions and answers were adapted by a human annotator.	Exact	Exact String Match
Figurative Speech Explanation	Images come from various websites. Questions were created by a human annotator.	Open	GPT-4o as Judge
Muma Theory Of Mind Social Goal	Images and labels come from the MuMA-ToM dataset (Shi et al., 2024). Questions and answers were adapted by a human annotator.	Contextual	Simple String Match
Muma Theory Of Mind Belief Of Goal	Images and labels come from the MuMA-ToM dataset (Shi et al., 2024). Questions and answers were adapted by a human annotator.	Contextual	Simple String Match
Hashtag Recommendation	Images and hashtags come from various social media websites. Questions were created by a human annotator.	Structured	Set Precision

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Dish Ingredient Match	Images and labels come from the HelloFresh website. Questions were created by a human annotator.	MC	Exact String Match
Music Sheet Sentiment	Images are music sheets posted to Noteflight. Questions and answers were created by a human annotator.	Exact	Exact String Match
Music Sheet Author	Images are music sheets posted to Noteflight. Questions and answers were created by a human annotator.	Exact	Exact String Match
Music Sheet Note Count	Images are music sheets posted to Noteflight. Questions and answers were created by a human annotator.	Numerical	Exact String Match
Music Sheet Format Qa	Images are music sheets posted to Noteflight. Questions and answers were created by a human annotator.	Numerical	Exact String Match
Orchestra Score Recognition	Images come from various websites. Questions were created by a human annotator.	Structured	Exact String Match, Simple String Match
Music Sheet Name	Images are music sheets posted to Noteflight. Questions and answers were created by a human annotator.	Exact	Exact String Match
Insect Order Classification	Images and labels come from the BIOSCAN-1M dataset (Gharaee et al., 2024). Questions and answers were adapted by a human annotator.	Contextual	Simple String Match
Signage Navigation	Images come from various websites. Questions and answers were created by a human annotator.	Exact	Exact String Match
Song Title Identification From Lyrics	Screenshots were taken by the human annotator on the Spotify Web Player. Questions and answers were created by the annotator.	Structured	Exact String Match
Knowledge Sign Recognition	Images come from various websites. Questions were created by a human annotator.	MC	String Set Equality Comma
Brand Logo Recognition And Elaboration	Images come from the FlickrLogo (Romberg et al., 2011) dataset and various websites. Questions were created by a human annotator.	Structured	Multi Ref Phrase

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Logo2k Same Type Logo Retrieval	Images come from the Logo2K+ dataset (Wang et al., 2020) dataset and various websites. Questions were created by a human annotator.	Structured	Exact Str Match Case Insensitive, Set Equality
Chinese Idiom Recognition	Images come from various websites. Questions and answers were created by a human annotator.	Exact	Exact String Match
Multi Lingual Ruozhiba Explanation French	Some images and labels are from the COIG-CQIA dataset (Bai et al., 2024) and some images are from Baidu Tieba and annotated by a human annotator.	Open	GPT-4o as Judge
Multi Lingual Ruozhiba Explanation Arabic	Some images and labels are from the COIG-CQIA dataset (Bai et al., 2024) and some images are from Baidu Tieba and annotated by a human annotator.	Open	GPT-4o as Judge
Multi Lingual Ruozhiba Explanation Spanish	Some images and labels are from the COIG-CQIA dataset (Bai et al., 2024) and some images are from Baidu Tieba and annotated by a human annotator.	Open	GPT-4o as Judge
Multi Lingual Ruozhiba Explanation English	Some images and labels are from the COIG-CQIA dataset (Bai et al., 2024) and some images are from Baidu Tieba and annotated by a human annotator.	Open	GPT-4o as Judge
Multi Lingual Ruozhiba Explanation Japanese	Some images and labels are from the COIG-CQIA dataset (Bai et al., 2024) and some images are from Baidu Tieba and annotated by a human annotator.	Open	GPT-4o as Judge
Multi Lingual Ruozhiba Explanation Russian	Some images and labels are from the COIG-CQIA dataset (Bai et al., 2024) and some images are from Baidu Tieba and annotated by a human annotator.	Open	GPT-4o as Judge
Font Recognition	Images and labels are taken from Identifont. Questions are created by a human annotator.	Exact	Exact String Match
Traffic Accident Analysis	Images and labels are taken from Jia Kao Bao Dian. Questions are created by a human annotator.	Open	GPT-4o as Judge
Multiple States Identify Asia	Images come from various websites and were edited by the annotator. Questions and answers were created by a human annotator.	Contextual	Sequence Accuracy Case Insensitive

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Multiple States Identify Americas	Images come from various websites and were edited by the annotator. Questions and answers were created by a human annotator.	Contextual	Sequence Accuracy Case Insensitive
Multiple States Identify Europe	Images come from various websites and were edited by the annotator. Questions and answers were created by a human annotator.	Contextual	Sequence Accuracy Case Insensitive
Multiple States Identify Africa	Images come from various websites and were edited by the annotator. Questions and answers were created by a human annotator.	Contextual	Sequence Accuracy Case Insensitive
Worldle	Images and labels are taken from Worldle Daily, a free Geoguessr alternative. Questions and answers are created by a human annotator.	Structured	Exact String Match
Location Vqa	Images and labels come from various websites. Questions were created by a human annotator.	Exact	Exact String Match
Vibe Eval Open	Images and labels come from the Vibe-Eval dataset Padlewski et al. (2024). Questions were created by a human annotator.	Contextual	Multi Ref Phrase
Vibe Eval Phrase	Images and labels come from the Vibe-Eval dataset Padlewski et al. (2024). Questions were created by a human annotator.	Open	GPT-4o as Judge
Ancient Map Understanding	Images and labels come from various websites. Questions were created by a human annotator.	Exact	Exact String Match
Rocks Samples Compare	Images and labels come from ChinaNeolithic.com's online rock store. Questions were created by a human annotator.	Contextual	Simple String Match
Painting Qa	Images and labels come from the MMMU benchmark Yue et al. (2024a). Questions and answers were adapted by a human annotator.	Exact	Exact String Match
Art Explanation	Images come from various websites. Questions were created by a human annotator.	Open	GPT-4o as Judge

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Memorization Chinese Celebrity	Images and labels come from various websites. Questions were created by a human annotator.	Structured	Multi Ref Phrase
Memorization Papers	Images and labels come from various websites. Questions were created by a human annotator.	Structured	Simple String Match
Memorization Famous Treaty	Images and labels come from various websites. Questions were created by a human annotator.	Structured	Exact String Match, Multi Ref Phrase
Memorization Indian Celebrity	Images and labels come from various websites. Questions were created by a human annotator.	Structured	Exact String Match, Multi Ref Phrase
Soccer Offside	Images come from various websites. Questions were created by a human annotator.	MC	Exact String Match
Deciphering Oracle Bone	Images and labels come from the "Deciphering Oracle Bone Language with Diffusion Models" paper (Guan et al., 2024). Questions were created by a human annotator.	Exact	Exact String Match
Kvqa Knowledge Aware Qa	Images and labels come from the MapQA dataset (Chang et al., 2022). Questions and answers were adapted by a human annotator.	Contextual	Simple String Match
Character Recognition In Tv Shows	Screenshots were taken by the human annotator on the Amazon Prime Video webpage. Questions and answers were created by the annotator.	Contextual	Set Equality
Actor Recognition In Movie	Screenshots were taken by the human annotator on the Amazon Prime Video webpage. Questions and answers were created by the annotator.	Exact	Exact String Match
Landmark Recognition And Qa	Images and labels come from the Landmark v2 dataset (Weyand et al., 2020). Questions and answers were adapted by a human annotator.	Structured	Exact String Match, Multi Ref Phrase, Near Str Match
Famous Building Recognition	Images and labels come from various websites. Questions were created by a human annotator.	Structured	Exact Str Match Case Insensitive, Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Landmark Check Two Images	Images and labels come from the Landmark v2 dataset (Weyand et al., 2020). Questions and answers were adapted by a human annotator.	Structured	Exact Str Match Case Insensitive
Defeasible Reasoning	Images and labels come from various websites. Questions were created by a human annotator.	Open	GPT-4o as Judge
Poetry Limerick	Images come from various websites. Questions and evaluation constraints were created by a human annotator.	Open	Constrained Generation
Poetry Shakespearean Sonnet	Images come from various websites. Questions and evaluation constraints were created by a human annotator.	Open	Constrained Generation
Poetry Custom Rhyming Scheme	Images come from various websites. Questions and evaluation constraints were created by a human annotator.	Open	Constrained Generation
Poetry Acrostic Alliteration	Images come from various websites. Questions and evaluation constraints were created by a human annotator.	Open	Constrained Generation
Poetry Haiku	Images come from various websites. Questions and evaluation constraints were created by a human annotator.	Open	Constrained Generation
Poetry Petrarchian Sonnet Optional Meter	Images come from various websites. Questions and evaluation constraints were created by a human annotator.	Open	Constrained Generation
Poetry Acrostic	Images come from various websites. Questions and evaluation constraints were created by a human annotator.	Open	Constrained Generation
Ascii Art 30	Images come from various websites. Reference ASCII art images were created using the ASCII Art Archive's "Image to ASCII Art" tool.	Contextual	ASCII Art GPT-4o Judge
Mathematics			
Graph Shortest Path Kamada Kawai	Data collected from Visual Graph Arena Dataset by human annotator, and the questions and answers are adapted to match strings	Numerical	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Graph Shortest Path Planar	Data collected from Visual Graph Arena Dataset by human annotator, and the questions and answers are adapted to match strings	Numerical	Exact String Match
Graph Connectivity	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	Structured	Exact String Match
Graph Theory	Data collected from MathVision (Wang et al., 2024b), and the questions and answers are adapted by human annotator	Exact	Exact String Match
Graph Isomorphism	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	MC	Exact String Match
Graph Hamiltonian Cycle	Data collected from Visual Graph Arena Dataset by human annotator, and the questions and answers are adapted to match set precision	Structured	Exact String Match, Set Precision
Graph Hamiltonian Path	Data collected from Visual Graph Arena Dataset by human annotator, and the questions and answers are adapted to match set precision	Structured	Exact String Match, Set Precision
Graph Chordless Cycle	Data collected from Visual Graph Arena Dataset by human annotator, and the questions and answers are adapted to match strings	Numerical	Exact String Match
Topological Sort	Data collected from screenshots by human annotator	Structured	Set Equality
Graph Maxflow	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	Numerical	Exact String Match
Scibench Calculus Wo Solution	Data collected from Scibench (Wang et al., 2023b)	Numerical	General Single Numerical Match
Clevr Arithmetic	Data collected from Clevr (Johnson et al., 2017)	Numerical	Exact String Match
Iconqa Count And Reasoning	Data collected from IConQA (Lu et al., 2021), with annotation refractered from the original IConQA dataset	Numerical	Multi Ref Phrase
Number Comparison	Data collected from screenshots by human annotator	Numerical	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Math Exams V	Data collected from MMMU-Pro (Yue et al., 2024b), and the questions and answers are adapted to match numerical data	MC	General Single Numerical Match
Theoremqa	Data collected from screenshots by human annotator	Contextual	Boxed Single Numerical Match
Math	Data collected from screenshots by human annotator	Numerical	Boxed Single Numerical Match
Math Parity	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	MC	Exact String Match
Math Breakpoint	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	Numerical	Exact String Match
Math Convexity Value Estimation	Data collected from IsoBench (Fu et al., 2024b), and the questions and answers are adapted by human annotator	Structured	Exact String Match, Number Rel Diff Ratio
Geometry Reasoning Count Line Intersections	Data collected from Vision language models are blind (Rahmanzadehgervi et al., 2024), and the questions and answers are adapted by human annotator	Structured	Exact String Match
Geometry Length	Data collected from MathVision (Wang et al., 2024b), and the questions and answers are adapted by human annotator	Contextual	General Single Numerical Match
Geometry Reasoning Nested Squares	Data collected from Vision language models are blind (Rahmanzadehgervi et al., 2024), and the questions and answers are adapted by human annotator	Structured	Exact String Match
Geometry Transformation	Data collected from MathVision (Wang et al., 2024b), and the questions and answers are adapted by human annotator	Contextual	General Single Numerical Match
Geometry Reasoning Overlapped Circle	Data collected from Vision language models are blind (Rahmanzadehgervi et al., 2024), and the questions and answers are adapted by human annotator	Structured	Exact String Match
Geometry Area	Data collected from MathVision (Wang et al., 2024b), and the questions and answers are adapted by human annotator	Numerical	Exact String Match

Table 18 – continued from previous page

Task Name	Source Description	Output Format	Metrics
Geometry Reasoning Grid	Data collected from Vision language models are blind (Rahmanzadehgervi et al., 2024), and the questions and answers are adapted by human annotator	Structured	Exact String Match
Polygon Interior Angles	Data collected from screenshots by human annotator	Numerical	Angle Seq Float Rmse
Geometry Solid	Data collected from MathVision (Wang et al., 2024b), and the questions and answers are adapted by human annotator	Contextual	General Single Numerical Match
Geometry Analytic	Data collected from MathVision (Wang et al., 2024b), and the questions and answers are adapted by human annotator	Contextual	General Single Numerical Match
Geometry Descriptive	Data collected from MathVision (Wang et al., 2024b), and the questions and answers are adapted by human annotator	Contextual	General Single Numerical Match
Counterfactual Arithmetic	Data collected from screenshots by human annotator	Numerical	Exact String Match
Algebra	Data collected from MathVision (Wang et al., 2024b), and the questions and answers are adapted by human annotator	Contextual	General Single Numerical Match